

**Rethinking the Impact of “Bad Press” in Politics: Testing an Identity Model of Partisan Media Effects**

by

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A dissertation submitted in partial fulfillment  
of the requirements for the degree of  
Doctor of Philosophy  
(Communication)  
in the University of Michigan  
2021

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## **Dedication**

All of this is because of you.

For Sam, always.

## **Acknowledgements**

As the old proverb goes: “It takes a village to raise a child.” Although I do not have children of my own, I believe this phrase can be applied to any significant human accomplishment. In both very big, and very small ways, the conversations, words of encouragement, advice and mentorship from those in my personal and professional community have played an integral role in my writing of this dissertation and completing the degree. While I will attend to very specific people here, I’d like to thank all the acquaintances, friends, colleagues, and especially teachers who have brought positivity to my life. You may not know, but even the smallest of gestures have helped me get to where I am today.

First, I’d like to thank those who have supported me the longest – my family. My grandparents Gerald and Marilyn Dewan dedicated most of their adult life to supporting their children, and then their grandchildren, in pursuing every possible opportunity for education. In both a very tangible sense, and in a spiritual sense, they created a family culture centered around the value of education in opening doors in our lives. Without them, I don’t know that I would have considered graduate school nor successfully completed it, and I am forever grateful.

My parents, Dave and Cheryl Bachleda, doubled down on this tradition by providing me uninhibited mentorship and love throughout my academic pursuits. From a very young age they encouraged me to question assumptions in society, to lean into my curiosities and to never fear well-reasoned debate. My natural talents were merely a starting point – this environment you created was what allowed my abilities to flourish. In other words, you made this academic achievement conceivable for me.



My siblings, Jill and Dan, have also been a constant source of love and encouragement. Thank you for going through all of life's challenges before me (including learning accounting, Jill), and for being generous with your advice and wisdom when my turn comes around. A special thank you as well to all my cousins, aunts/uncles, and other relatives who have directly supported this pursuit with discussions about politics or research, and to those who simply texted me with words of encouragement and pride – this includes all the Cassins, Bachledas, Carpenters and Moseleys. Although my grandparents, Joseph and Cecilia Bachleda, were not alive while I pursued this degree, the foundation of love and support they instilled among our family has had a significant impact in my life. I know they would be proud.

I'd next like to thank the Fioronis – Joe, Lynette, Maddie, Nick and Sarah (R.) – for welcoming me into your family as one of your own. Throughout my graduate school experience, you have all been a source of positivity and provided often-needed laughter, especially when I was feeling challenged and discouraged. Thank you, Lynette and Joe, for your generous investment and persistent belief in me, and most importantly, for helping me learn how to maintain that belief in myself.

Friends, some would say, are the family you choose. Words do not feel sufficient to express how deeply grateful I am for you, Anna Mortell and Jessica Rosenfield. Many, many times I was set on giving up on this endeavor. You pulled me out of that hole by showing me that it is ok to struggle, and by reminding me that I have more strength and perseverance inside of me than I realize. We can do hard things.

Next, I'd like to thank my "Ann Arbor" crew – Cristina Jarbou, Alison Todak, Lou Sheridan, Christine Gordon, Tom Frank and Jessica Henry (and respective partners). My time at the University of Michigan, starting with the Center for Entrepreneurship and ending with the

Ph.D., was one of the most challenging and formative periods of my life. You all played an essential role in helping me discover my (adult) self with lots of love... and lots of laughs. I can't thank you enough for your support of me not only in pursuing this degree, but in all areas of my life.

I'd also like to thank the "South Bend" crew – especially Aubrey McCormick, Hayley Lindahl, Molly Lawrence, Nicole Tally and Lindsey Jacobs. Though we haven't known each other long, our fast friendship during these past (crazy!) two years were critical to me completing the degree. You all bore witness to the most challenging period of this journey – being isolated, writing the dissertation during a global pandemic. Our walks, talks, and even the smallest of texts of encouragement truly got me through.

There are many teachers, colleagues and administrators who made this dissertation possible as well. First, I'd like to thank my committee members for their thoughtful feedback and encouragement throughout this process. Brian Weeks, you have been a central mentor to me from the moment I started the program. Thank you for your kindness, patience and generosity with your time and advice. Nick Valentino and Allison Earl – you both stood out to me first as exceptional teachers. You pushed me harder than most to challenge myself, the quality of my work and my assumptions. My dissertation, and my approach to research, is better because of your direct mentorship. Second, I'd like to thank other professors who made a positive impact on me both as teachers/mentors and as colleagues – Sonya Dal Cin, Nojin Kwak, Scott Campbell, Ted Brader, Josh Pasek, Ariel Hasell, Sol Hart and Amanda Lotz.

Thank you to all the members of the Political Communication Working Group throughout 2016 – 2021, the Institute of Social Research and the Center for Political Studies for the opportunities to grow and better my research. Thank you to the Rackham Graduate School,

the Department of Communication and Media, and the Howard R. Marsh Fellowship for providing me with funding necessary to complete my work and develop as a professional through conferences. Finally, a warm thank you to all the administrators – especially Amy Eaton, Dustin Hahn, Adrienne Janney, Melissa Bauernfeind and Sandro Faber-Bermudez – for running an exceptional program and for always prioritizing graduate student success.

I am also deeply appreciative to all the graduate students who have worked tirelessly to create a community of support and camaraderie. Starting with my cohort – Yuval Katz, Ta’Les Love, Youngrim Kim, Fan Liang and Megan Steiner – going through the thick of it with you was such a gift. You are all incredible scholars and extremely bighearted, and I wouldn’t have made it through prelims, first year projects or adjusting to the insanity that is graduate school without you. I’d also like to acknowledge Dan Lane, Stewart Coles, Dia Das, Ian Hawkins, Sage Lee, Sriram Mohan, Matea Mustafaj, Jessica Roden, Cait Dyche, and Jana Wilbricht. From advice on teaching and navigating the department to being in classes together to grabbing a drink at conferences, you all have made my experience at Michigan so much richer, thank you. I’d like to further thank Guadalupe Madrigal and Gavin Ploger for your thoughtful feedback on my work in our lab group(s); Lauren Hahn for being a friend full of sunshine and kindness; and Sedona Chinn for being the best mentor I could have hoped to be paired with, walking me through every step of this program with empathy. Finally, Dan Hiaeshutter-Rice, thank you, friend, for making life’s “miseries” tolerable with a drink and some laughs (...and for always getting me out of a bind in R).

Finally, I am ever grateful for the mentorship and friendship from my advisor, Stuart Soroka. You taught me how to be a thoughtful and responsible scholar. You taught me how to be an engaging teacher. You taught me statistics, how to interpret data and how to code. And you

taught me to tirelessly pursue that which makes me happy. “Is this fun for you?” is a question, and an approach to life, that I will carry with me. Thank you.

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## Abstract

The rise in negativity in media coverage and campaign messaging in U.S. political elections is of pressing concern for scholars of political communication. Negative information has not only been shown to be more attention-grabbing than positive information, but there is also evidence that citizens respond to that information in diverse and often counter-intuitive ways. I argue our degree of attachment to political party groups, operationalized using the Social Identity Theory framework, is a useful tool to predict and understand these heterogeneous media effects.

Building on existing literature in psychology, I suggest that elections in the U.S. two-party system are a “high group threat” context where biased processing and affective reactions are likely to be provoked for those who strongly identify with a political party group. Next, I review growing evidence in political science supporting the conceptualization of partisanship as psychological attachment to a group in contrast to competing ideology- or attitude-focused theories. Finally, I argue that although communication studies work frequently uses Social Identity Theory (SIT) as a tool for understanding the mechanisms driving various predominant media effects, little research has *directly* applied SIT to the study of partisanship as a predictor (and moderator) of outcomes. In sum, I connect theory and evidence across three disciplines to suggest an improved and more potent approach to exploring identity-based heterogeneous media effects in politics.

I provide further substantiation of my approach using American National Election Studies data and tracking of media coverage tone over the course of five previous elections.

Strength of partisanship proves to be an important moderator of the impact of media tone on voter attitudes. For evaluations of in-party candidates, increased negative tone of coverage *increases* in-party voter feelings of warmth towards those candidates, and the effect is amplified for the strongest partisans. Using these results as a springboard, I then present a novel measure of partisanship operationalized as the degree of psychological attachment to the political group. Subsequently, I field two surveys during the 2020 presidential election and find that the new measure (called PSIM) outperforms the most common existing measure of partisanship (PID) in predicting the hostile media effect, selective exposure behavior, and motivated reasoning among partisans. I also find evidence suggesting that PSIM is a useful tool for understanding heterogeneity in the impact of negative news on voter attitudes.

In sum, political partisans respond to negative media messages in diverse and biased ways depending on (a) the group dynamic at play and (b) the degree to which the partisan's identity is "attached" to the political group. I believe the new PSIM measure, and the results of my analyses, are useful to scholars of political communication as they may help them better (more acutely) navigate studying the tense communication climate in today's political elections. Although bias is deeply ingrained in human processing, I hope that continued research into patterns of bias and conditions where it becomes salient will, at a minimum, increase the public's awareness and, optimally, inspire improved techniques in overcoming it.

## Chapter 1 Revisiting the Definition of Partisan Identity

### Introduction

The 2016 presidential race has been argued to be one of the most negative campaigns in the U.S. – from public opinion of the candidates to the mainstream press’s coverage to straight up political scandal. Yet, the effect of that negativity *felt* like it was asymmetrical. On the one hand, the Clinton campaign seemed unable to recover from the problems with her “emails” (see Newport et al., 2016). On the other hand, then-candidate Trump maintained support (even from the evangelical, conservative right wing) despite the publication of a recording of him explicitly discussing sexually assaulting women *and* media stories reporting he was paying an adult film actress to keep quiet about an affair. Many pundits were surprised that his campaign not only survived such explosive scandals during an election cycle, but he also went on to win the presidency. This begs the question: Why does a negative scandal in the press seem to hurt or even end some candidates’ chances for success<sup>1</sup>, while other candidates are perfectly able to survive them<sup>2</sup>? I believe this calls into question the impact of “bad press” in politics.

It has become widely accepted that at the heart of an ideal democracy is a free, well-functioning press. The right to a press free of government control is outlined in the first

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<sup>1</sup> E.g., Hillary Clinton’s emails – 2016; John Edwards’ affair – 2008; Gary Hart’s affair – 1984; Gerald Ford’s “tamale” incident – 1976

<sup>2</sup> E.g., Roy Moore’s sexual assault allegations – 2018; Donald Trump’s recording and affair – 2016; Bill Clinton’s affair with Flowers and Lewinsky – 1992, 1998

amendment of the U.S. Constitution, for example. And the freedom of press is one of the cornerstones by which we rate the quality of democracies world-wide. The press serves as a conduit of information between citizens and government, and vice versa. But most importantly, it primarily functions to “help guard against abuses of power by officeholders” (Gurevitch & Blumler, 1990, 269).

Hence, media in modern democracy has taken up the mantle of being a “watchdog,” or *critical* of those in power. Reporting on wrong-doings, failures, corruption, scandal, and so on, that could be detrimental to citizens or society is a common goal among news media today. Ideally, as the public takes in this information they update or adjust their attitudes in line with their best interests. So, if the local press reports that a state senator is using tax-payer money to pay for family vacations, constituents might reconsider voting for him or her again.

In the abstract, this process seems simple enough. Yet, as is evident in the extensive literature on motivated reasoning and hostile media effects, the relationship between the press and citizens doesn’t necessarily work that way in practice. Recent polling shows that trust of media institutions has been at an all-time low, driven by citizens that fall on the right side of the political spectrum (Brenan, 2020). Scholars also find that in the face of damaging information about a political candidate or party, people often engage in biased information processing – either rejecting or counterarguing the information, or expressing defensiveness (e.g., Gunther & Liebhart, 2006). That is to say, attitude updating due to “watch dog” reporting doesn’t always work the way it is supposed to. What is the role of media in representative democracy, then, if critical stories about political leaders don’t achieve their intended impact on citizens’ attitudes? This is a pressing question for scholars of political media today.



In order to consider the long-term impact of biased processing of media messages on democracy, scholarship must first investigate the mechanisms and conditions that drive this phenomenon. Each of the chapters of this project attempt to do so, with the aim of advancing the study of political media effects with novel theoretical considerations and data. Overall, my argument rests on the idea that conceptualizing and properly measuring partisanship as a “social identity” attachment is a potent means of understanding media effects during elections in the U.S. I argue this approach provides an improved and more cohesive theoretical framework than currently exists in the literature – and one that better predicts heterogeneity in the impact of political media on voters.

## **Chapter Outline**

This first chapter will briefly overview connected theories in psychology, political science and communication as they relate to understanding the nature of political party attachment in the U.S. In political science, there is a growing body of work that connects partisanship to Social Identity Theory (SIT) in psychology (Tajfel, 1978). In communication, there is a significant body of work that connects biased media processing and effects to SIT as well, potentially via cognitive dissonance and other psychological mechanisms. My objective is to bring all this literature into conversation, and thus demonstrate that an SIT approach to measuring partisanship, in line with motivated reasoning theory, is a useful tool for political communication scholarship. I then use this theory to develop some general hypotheses about the impact of strength of attachment to political groups on media effects, which then shape analyses explored in the following chapters.

In Chapter 2, I use existing data from the American National Elections Studies (ANES) to test the impact of partisanship as moderator of media effects over the course of five U.S. presidential elections. I combine ANES time series surveys with a robust dataset of newspaper coverage of the five elections to trace the effect of media tone about the front-running presidential candidates and parties on voter favorability towards candidates. My aim is to (a) demonstrate the influence of media coverage on citizens during real election contexts and (b) provide a “proof of concept” of the SIT approach to studying political media effects. I find that changes in media tone do shift voter attitudes over the course of these elections, even when controlling for a wealth of other variables such as demographics, media use, political interest and variation in individual election year. Furthermore, strength of partisanship proves to be an important moderator of the effects. I find that positive attitudes about a partisan’s in-party candidate *increase* as negative coverage of the in-party increases. Conversely, the effect for out-party evaluations is in the direction one would expect – more negative coverage results in less positive attitudes towards the candidate. This is true for both Democrats and Republicans, in line with SIT and motivated reasoning, and the effect is amplified for the strongest identifying partisans. Although this chapter does not operationalize partisanship using SIT framework (as is the focus of the subsequent chapters), I present evidence that media mattered during real election contexts and that strength of identification with a political party influenced those effects in meaningful ways.

The first necessary step towards successfully operationalizing partisanship as social identity attachment is to develop and test measures of partisan social identity. Chapter 3 thus starts with a review of the extensive and complex literature on the measurement of social identity attachment in psychology. I find that these measures fall into one of two categories – universally

applicable to any group attachment or group-type specific – and that the majority of scholars argue social identity attachment is a multi-dimensional concept to measure. There are about 13 different conceptualizations of theory-driven underlying dimensions included across the body of work. I then review the few existing measures developed by Greene (2004), Huddy et al. (2015) and a few others that test SIT-focused measures of political partisanship specifically in the U.S.

I conclude that there is no clear theoretical pathway to guide the selection of one of the many (at least more than 20) existing survey indices. I thus turn to a data-driven exploration of the measurement of partisanship as social identity attachment. Drawing off 12 of the reviewed measures, I field the first wave of a two-wave survey including 37 different questions (covering all 13 theoretical dimensions) targeted at measuring the degree of identity attachment to political parties. Using principal components analysis to explore the relationships among questions, I find that nearly all fall onto one dimension. Furthermore, it appears that using the top 10 (and even the top 4) are sufficient in capturing nearly as much variance as the entire 37-question battery.

Finally, I demonstrate that this measure of partisan social identity attachment (called PSIM) is only partially correlated with the most commonly used measure of partisanship (called PID), and that within PID categories there is a good deal of variation in PSIM. The end result of this chapter is a novel measure of SIT-focused partisanship, that can be easily deployed in surveys, and that I hypothesize will outperform existing measures of partisanship in explaining political media effects.

Chapter 4 tackles this head on. I use data from the two-wave survey fielded during the 2020 presidential election to explore the predictive power of the new SIT-partisanship measure, PSIM, compared to PID on three predominant effects studied in political communication: the hostile media effect, selective exposure, and trust of counter-attitudinal information (i.e.,

motivated reasoning). I selected these three effects to showcase PSIM compared to PID, in part, because they all have historic theoretical ties to Social Identity Theory. Although, strikingly, much research in these sub-fields has not *directly* operationalized partisanship via SIT. I highlight a wealth of indirect evidence that points to the importance of the *degree* of psychological attachment to group identities in understanding these effects. My hypotheses for hostile media effects, selective exposure and motivated reasoning are all supported – PSIM offers, in almost every case, an improvement over PID. I then discuss future testing of the PSIM measure and potential applications in communication research going forward. My goal is that the work presented here can serve as a foundation for scholars to continue to explore the importance of psychological attachment to political group identities in understanding the unique ways in which citizens respond to group-threatening political contexts.

Chapter 5 offers a brief review of findings in the preceding chapters and presents an example of how PSIM could be further tested using more complex media effects models. Using the survey data from Chapters 3 and 4, I look at the role of PSIM and PID in moderating the impact of exposure to a negative news story about the in-party candidate on voter attitudes towards those candidates. In other words, I revisit the dependent variable examined in Chapter 2. The model for the moderating effect of PSIM (and PID) fails to reach significance, however. That said, there is a significant direct effect of PSIM on the outcome (and none for PID), and the interaction coefficients are in the predicted direction. Limitations due to the sample, experimental method and multicollinearity of the predicting variables are discussed. Finally, I conclude by discussing how my findings can serve to help us predict, navigate and understand the heterogenous impact of “bad press” in politics.

## Theoretical Background

### *Social Identity Theory and Group Threat*

First introduced by Tajfel (1978) and further developed by Tajfel & Turner (1979), Social Identity Theory (SIT) at its most basic level describes the psychological phenomenon of an individual defining her or his sense of self through membership to social categories in society (e.g., gender, sports team, nationality...political party). The theory posits that when a group identification becomes salient in a given context, efforts to preserve positive feelings and perceptions of the group are evoked, particularly when the *degree* of self-conceptualization via the group is deep. In other words, a threat to the group literally – i.e., power and resources – or symbolically – i.e., reputation and status in society – thus also introduces potential damage to the individual on those levels as well.

Tajfel, Turner and decades of subsequent scholarship find that psychological attachment to groups shape the way people process information, the attitudes people hold, and their behavior. Furthermore, Turner & Giles (1981) argue that via the process of group stereotyping, people with strong group attachment also come to define themselves in *contrast* to other (or opposing) groups as well. Hence, triggers of group threat are not limited to negativity solely directed at the in-group. They also occur as the result of perceived (or existing) competition between groups.

For the purposes of this project, I will explore the importance of *degree* of psychological attachment to a group as a lens through which SIT can be usefully applied to studying political media effects. My hypotheses are situated within the taxonomy of the *Self and Social Identity* developed by Ellemers, Spears & Doosje (2002). These authors describe SIT as the “content” of identity and argue that the impact of SIT in academic research is contingent on the strength of

ties to that group: “When collective identities are concerned, the level of commitment to a particular group or category determines how group characteristics, norms or outcomes will influence the perceptual, affective and behavioral responses of individuals belonging to that group” (164). They create a framework for using SIT to predict outcomes by varying levels and types of threat combined with levels of commitment to a group identity.

Ellemers et al. (2002) assert that effects of SIT are entirely contingent on context. “The basic assumption here is that the relevant social context determines which categorization seems most suitable to provide meaningful organization of social stimuli, and hence which identity aspects become salient as guidelines for the perceptions and behavior of those who operate within that context” (165). In other words, identities must be triggered in the environment for them to become salient enough to influence people. These contexts are also critically important in that contexts eliciting positive group perceptions create a sense of security, and while contexts eliciting negative group perceptions create a sense of threat. The response of the individual is therefore shaped by the valence of these perceptions.

The impact of the signals from social contexts on identifiers, however, is not universal. Ellemers and authors further theorize that the *degree of commitment* to the identity interacts with the nature of the context, leading to heterogeneous outcomes. Thus, they propose that three contexts – no threat, individual-directed threat and group-directed threat – processed by identifiers with low versus high commitment levels lead to six unique outcomes (see full taxonomy in Ellemers et al., 2002, Table 1, 167) ranging from non-involvement or non-response to intensely biased information processing and behavior. To summarize: “...responses should not be considered in isolation...Consideration of the different underlying goals and motives

associated with combinations of self and contextual conditions is essential to explain why superficially similar as well as different response patterns emerge” (179-180).

I believe the third type of threat category in Ellemers et al.’s (2002) taxonomy, “group-directed threat” is most applicable to the context of media coverage during U.S. political elections. The authors characterize group-directed threat as a context in which the group’s value, via status, resources, power, morality or reputation, is put in question. In every election cycle in the U.S., the country has two competing and deeply entrenched political groups vying for positions of power and influence, and access to resources. This competition plays out in a very public way, through 24/7 news coverage. One group is fighting to maintain their position of influence while the other is working to convince the public to choose their group to lead, instead. Much of John Geer’s work shows that as time has gone on, the content of U.S. political campaign communications has become more focused on attacking a candidate’s opponent (or the competing party), and media tone is growing more negative (see e.g., Geer, 2012). Thus, I believe this to be a context ripe with opportunities for the perception of the political group’s value, status and positive reputation to be put at risk.

Within the group-directed category, Ellemers et al. (2002) predict that low-commitment and high-commitment identifiers respond differently to threatening stimuli. They argue that low-commitment identifiers will attempt to emphasize the heterogeneity of the group or even “hide” their identification with the group in an effort to prevent the negative perception of the group affecting perceptions of themselves. In some extreme cases, low-commitment identifiers may even abandon the group altogether. On the other hand, the authors suggest that high-commitment identifiers will challenge the source of the threat or attempt to change the status configuration. It will likely draw out further expressions of loyalty to the group and increased anger or contempt

feelings towards the out-group (or weaker groups). Those highly attached to the group will be more inclined to “defensive reactions” (Ellemers et al., 2002, 177).

These predictions can be directly applied to the group-directed threat context of a political election. I believe the media – both news coverage and campaign communication – is the essential medium through which the “threat” (bringing into question positive perceptions of the in-group) is delivered. Accordingly, one could predict that low-commitment versus high-commitment identifiers will respond very differently to those messages. Low identifiers may simply ignore the information, down-play their identification with others or even be more open to updating their perceptions of the group in the direction of the tone of coverage. High identifiers, on the other hand, are likely to engage in biased processing and behaviors, or work to resist and discredit the information.

What is described here is a succinct framework for understanding the very common heterogeneities already evident in current research on political communication effects. Throughout the rest of this project, I highlight this existing literature and present my own original findings, that map on well to Ellemers and authors’ taxonomy.

### *Partisanship as Social Identity*

The mechanisms underlying political partisanship in the United States have been long debated in political science research. On the one hand, *The American Voter* sparked a body of work which conceptualizes partisanship as a stable, psychological attachment; a lens through which citizens act and think politically (Campbell et al., 1960). On the other hand, work such as Fiorina's (1981) dynamic model of retrospective evaluation argues that partisanship is a summation of attitudes, where preferences are constantly being updated with new information and experiences. Recent scholarship has attempted to blend these two perspectives - suggesting



that Republicans approach politics ideologically and Democrats do so through social group dynamics (Grossmann & Hopkins, 2016). Huddy & Bankert (2017) distinguish these approaches using the terms “expressive partisanship” (for social identity attachment) and “instrumental partisanship” (for attitude updating), to demonstrate that this distinction can lead to different motivations for political behaviors. Much existing literature (which continues to grow) falls in line with the Social Identity Theory-approach, however – including the compelling evidence presented by Green et al. (2002) in *Partisan Hearts and Minds*, Huddy et al.’s (2015) social identity model of expressive partisanship, Iyengar et al.’s (2012) “affect” not ideology, and Mason’s (2018) recent work, *Uncivil Agreement: how politics became our identity*. The empirical data at the core of these projects demonstrate that attachment to a political party as a group identity not only withstands variability in evaluations of political leaders and conditions (Green et al., 2002), but also has more power than partisanship as ideology or a collection of attitudes in predicting political behaviors (e.g., Huddy et al., 2015; Mason, 2018).

In response to the concept of voter learning theory, Green et al. (2002) compare the stability of partisan attachment to both general party and presidential evaluations over multiple decades. They find that while the public quite visibly adjusts its evaluations of their party’s competence and the performance of the party’s leader in response to the political and economic conditions of the time, partisan identification is substantially more stable than these attitude fluctuations (Ch. 5). This, they argue, is in direct contradiction to work by Achen (1992), who finds partisan attachment is connected to a collection of evaluations of political conditions and actions of representatives as they benefit or hurt the interests of the citizen. Furthermore, Green et al. (2002) conclude that “when opinion is tracked over time to control for preexisting tastes and beliefs, different partisan groups seem to be similarly influenced by information” (136) when

evaluating political performance. Yet, the fact that partisan identification remains consistent over this period indicates that there is some rooted, stable party attachment that weathers outside influence.

There are many other compelling projects in political science that indirectly point to a connection between SIT and the nature of political partisanship. Groenendyk (2012), for example, finds that “partisans rely on their attitudes towards the opposition party to justify their identity when their attitudes towards their own party would otherwise conflict with it” (454). Clifford (2017) shows that variation in strength of partisanship was strongly predicted by “group loyalty,” even when controlling for other factors such as demographics, patriotism and ideological extremity. Barber & Pope (2019) further report that loyalty to the political parties predicted acceptance of cues from party leadership in *both* conservative and liberal-leaning directions. They assess that for some people, loyalty to the group trumped ideological attitudes. Mason (2018) provides compelling evidence that partisan identity is becoming more strongly connected to and predicted by other identities (such as religion and gender), resulting in a deep “homogenization” of the parties beyond ideological beliefs. And finally, Arieli et al. (2019) find that people evaluated the actions of the in-group political candidate as more trustworthy and as intended to benefit the country while they interpreted those same actions by out-group candidates as self-serving. In sum, recent data is pointing towards partisanship as more than just a summation of what you think, but rather a deeply affective connection to the group.

A smaller, but equally compelling, group of research has taken up the SIT framework to measuring and exploring political partisanship more directly. Greene (2004) was one of the first scholars to adopt a social identity group attachment measure from work in psychology (Mael & Tetrick, 1992) and apply it to partisanship. He finds that this 10-item measure significantly

predicted various political outcomes better than previous measures of partisan strength. Huddy et al. (2015) build off Greene's work and developed their own abbreviated SIT-focused partisanship measure, finding that it outperformed ideological affiliation and traditional measures of partisanship in predicting past electoral activity and current/future campaign participation across three different samples of data. Similarly, Devine (2015) adopts Mael and Tetrick's IDPG scale to measure psychological attachment to ideology (conservative/liberal) calling the measure Ideological Social Identity (ISI). He finds overall that both self-identified conservatives and liberals score higher on the ISI scale than moderates, and that exposure to stimulus about election results increased conservative and moderate's ISI – which the authors suggest may be related to perceptions of threat. And on an aggregate, international scale, Westwood et al. (2018) demonstrate using data from the U.S. and other European democracies (i.e., Great Britain, Belgium and Spain) that citizens are more strongly attached to political party identities than they are to other social groups that may be represented by the parties; specifically, religion, language, ethnicity and region. Partisan ties also predicted greater distrust of the outgroup than these other identities, resulting in more polarization. The results were consistent across the four democracies.

A social identity-attachment approach to studying partisanship, which allows for degrees of attachment to vary, clearly predicts variation in the effects of partisanship on voter attitudes and behaviors. Leeper & Slothuus (2014) argue that partisanship's role in public opinion may at times be an emotional, "effortless" attachment in guiding citizen thoughts and actions, or it can function more along the lines of Downs (1957) work as simply a heuristic used to make more efficient political decisions. This kind of variation, fits well with the SIT context/commitment conditions outlined in work in psychology. A core motivation of this project, in fact, stems from

the idea that partisanship can take many forms for different people, and that those differences are meaningful when trying to predict how media in particular affect voters.

### *Political Party Identity and Information Bias*

When studying politics in the U.S., the use of partisanship as a predictor of outcomes is entrenched in the political science literature. It has similarly become a pervasive variable examined across communication subfields. I highlight a brief review of that literature here, followed by more in-depth reviews in Chapters 2 and 4. My objective here is two-fold. First, I aim to demonstrate that Social Identity Theory and partisanship have already converged theoretically in political communication scholarship over the past few decades. That said, there has been little work which operationalizes the measure of partisanship directly in line with this theory in communication. Second, and despite this fact, I highlight that much of this existing work provides indirect evidence of the group identity attachment nature of partisanship. Together, these set the stage for my novel testing of the impact of partisan social identity attachment on media effects outcomes.

Festinger's (1957) theory of cognitive dissonance has become a common framework for studying the relationship between information exposure and attitudes in communication scholarship. He argues that people feel psychological (and physiological) discomfort when faced with information (or situations) that are inconsistent with or opposing to existing beliefs. This motivates people to engage in mental processes and behaviors that aim to reduce these feelings of discomfort. Subsequent scholarship studies related patterns of behavior like the preference for positive hypothesis testing – our natural inclination to confirm rather than disconfirm a hypothesis – and similarly, confirmation bias – the motivation people have to confirm, through information seeking or information interpretation, what they already believe to be true (Klayman,

1995). Furthermore, Kunda (1990) explains, “There is considerable evidence that people are more likely to arrive at conclusions that they want to arrive at, but their ability to do so is constrained by their ability to construct seemingly reasonable justification for these conclusions” (480).

In line with the theory of cognitive dissonance, previous research has also demonstrated that people are drawn to select information that affirms existing beliefs. Stroud (2008) finds that political identities and strength of prior political attitudes, specifically, are a consistent and powerful predictor of media selection behavior across many media platforms (what’s referred to as *selective exposure*). As Slater (2015) further explains, people seek out attitude congruent information in order to reinforce political identities and attitudes, creating a “positive feedback loop.” This behavior can be especially activated when a social identity is threatened (like during a political election, for example). Slothuus & de Vreese (2010) find that “citizens respond more favorably to an issue frame if sponsored by a party they vote for than if the frame was promoted by another party” (642), demonstrating that this kind of information preference may have important effects on attitudes as well.

That doesn’t mean, however, that partisans are only surrounded by attitude-affirming information. Most research on this topic makes clear that even in the face of selective preferences, people are frequently exposed to cross-cutting or contradictory information that may bring about cognitive dissonance. Frimer et al. (2017) find that both strong Democrats and Republicans are equally as likely to report feelings of discomfort or frustration in the face of conflicting political views. So, how would one expect partisans to react to counter-attitudinal information? There’s strong evidence to suggest that this brings about biased processing called *motivated reasoning*, where citizens develop rationalizations designed to reach the desired

conclusion of confirming a pre-existing attitude. This can both be driven by an “illusion of objectivity,” i.e., an attempt to rationally “muster up the evidence necessary to support it” (Kunda, 1990, 482 – 483), or through more affective processing, or by discrediting and distrusting any uncongenial information. Lodge & Taber (2013) describe this as people wanting to think what they feel, allowing passions and emotions to drive cognitive justification for attitudes.

Motivated reasoning has been well-studied in the context of politics. Redlawsk (2002) finds that when people are exposed to information about their own party’s candidate that is incongruent with their attitudes, they take longer to process it and may actually result in supporting that candidate *more* than previously. This could be attributed to threat-provoked identity defensiveness of the in-group or simply rejection of the information altogether. Taber & Lodge (2006) demonstrate that people tend to evaluate attitudinally congruent arguments as stronger, counterargue in the face of disconfirming information, and uncritically accept confirmatory information. Herrmann (2017) also finds that the more strongly people attach to the United States as a “social identity” the more likely they are to warp and rationalize information about globalization to support their existing beliefs about the subject.

It is evident that voters prefer information in line with their beliefs and “operate as motivated reasoners, attempting to hold to their existing positive evaluation by using any one of a number of processes to explain away new incongruent information” (Redlawsk et al., 2010, 564). These biases may even fuel skepticism and distrust of the media broadly. As Gunther & Liebhart (2006) explain, partisans are much more likely to report information that is contrary to their opinions as *inaccurate*. Even when exposed to neutral information, seeing the source of a story can evoke resistance and perceptions of biased reporting among partisans (Gunther &

Schmitt, 2004). This is often described as *hostile media effect*, or “the tendency for people who are highly involved in an issue to see [any] news coverage of that issue as biased, particularly as biased against their own point of view” (Gunther et al., 2001, 296). And often, it is just the simple perception, through a partisan identity lens, that evokes this kind of negative reaction to media content, regardless of the nature of the content (Perloff, 2015).

The very apparent biases in people’s information processing of media content, as directly influenced by partisanship, fits well into the idea of party attachment operating as an identity. As Cooper & Stone (1999), point out, however, most research on cognitive dissonance and biased reasoning focuses on individual-level effects. The authors posit that group social identity may better help scholars understand the conditions when dissonance takes place and serve as a means of predicting how people overcome it. They suggest, “One advantage of Social Identity Theory is that it makes clear the notion that people constantly negotiate their identity and that their identity is inextricably intertwined with the multiplicity of their social groups. Thus, group membership is a consistently available cognitive category that may come into play as a person prepares to act in a variety of [potentially dissonant] situations” (151 – 152). In the realm of politics where party group attachment and attitudes about policies tend to be established rather early in life, (e.g., Sears & Valentino, 1997; Jennings et al., 2009; Thorson et al., 2016) and remain relatively stable over time (Green et al., 2002), the biases provoked by dissonance may thus pose a clear threat to the rational attitude updating one would hope voters experience when exposed to “watchdog” media content, for example.

The intersection of SIT, partisanship and media effects rests on the idea that people are attached to political groups at a psychological level, and that the degree of attachment influences how people react to media messages about their group – particularly when that message brings

about a group-directed threat context. Turner & Giles (1981) present a helpful visualization of this idea when they say, “individuals internalize group products [i.e., media] such as slogans, norms, values and stereotypes...and so achieve shared frames of reference which regulate and coordinate their actions and attitudes” (35). I believe conceptualizing partisanship as identity-based fits nicely with the theory and data on biased information processing in communication reviewed above. I intend to expand the literature by applying this framework more directly to explore heterogeneous media effects.

### **A Social Identity Approach to the Study of Media Effects**

The identity-driven theory of media effects presented here establishes that when there is strong identity attachment to a group (in this case, a party), we should expect the effect of media on attitudes to be influenced by the degree of this attachment. If one perceives the Democratic party or Republican party as one’s “group,” then, in-group members will have (a) strong prior attitudes in line with that group’s beliefs and (b) motivation to advance the status, power and resources of the in-group, (c) particularly in the face of threatening information or contexts. I argue that this dynamic is particularly potent during political elections in the U.S. when the two political parties have either the risk of losing current power, or the opportunity to gain it, with the entire competition played out via media messages easily accessible to the public. For identity-based partisans, then, this would be a high-threat environment where biases are likely to be especially prevalent.

However, it is worth considering that not *everyone* adopts a political party group as a form of “identity.” Huddy & Bankert (2017), for example, note that while there is clear evidence of growing affective or emotion-driven politics in America, that does not mean it’s universal.



Therefore, the application of SIT to partisanship must capture a continuum of identification – using *degree* of attachment as a means of distinguishing *how* people are identifying with these groups. This kind of measure of variation of group attachment may be a better tool to explore variation in effects. I hypothesize broadly that this is very likely the case for studying the often heterogeneous impact of political media on citizens’ attitudes, which I outline in more detail below.

For those who have pre-existing *strong identity-based attachments* to political parties, I predict that it is unlikely that group-threatening media coverage of candidates will fundamentally change vote preferences (see e.g., Phillips et al., 2008). Yet, information reported by the media that evokes a group threat (such as a scandal, losing in the polls, public blunders, etc.), that may be intended to check those in power, could backfire for this group of citizens. Strong identifiers are more likely to resist that information or even distrust it, rather than think critically about the candidate or adjust their attitudes. Along those lines, I also predict exposure to positive information about in-group candidates has little influence on attitudes due to a “ceiling” effect – where the strength of the prior attitude is already at too high a threshold. Conversely, and in line with the framework proposed by Ellemers et al. (2002), in a group-threat situation, I predict that people with *low-attachment* to political groups who are exposed to media attacking their in-group may be more likely to shift their attitudes in line with the direction of the coverage. This still may not fundamentally change their overall attitudes towards the party or candidate, however, unless an “affective threshold” is reached (see, Redlawsk et al., 2010). **To summarize, I hypothesize that partisan social identity attachment will not only be a better predictor of media effects, but it will also be an important moderator of heterogeneous outcomes.**

It is important to note that political “identity” in the U.S. is not strictly limited to the Republican and Democratic parties. As of April 2021, Gallup estimates that about 44% of voters report themselves as an “Independent” compared to 25% Republican and 30% Democrat (Jones, 2021). Recent scholarship has been challenged by what it means when a respondent considers her or himself an Independent, however. Keith et al. (1992), for example, argue that independents are really closet partisans or “undercover partisans” (as does Abramowitz, 2014). Hawkins & Nosek (2012) find that Independents have implicit partisan leanings, and those leanings significantly predict their attitudes. More recently, Klar & Krupnikov (2016) argue that to identify as Independent is more complex, and that the motivations for rejecting partisan identification or “hiding” one’s political leaning may have to do with negative public perceptions of the parties – i.e., impression management. Independents are often presented positively in the media, the authors explain, as free thinkers, anti-establishment and critical players in determining elections, compared to the bickering and biased personas portrayed of Democrats and Republicans. Therefore, Independents may be (a) people who tend to vote towards one party – leaners – but view the parties themselves in a negative way or (b) people who actively identify as “anti-party” (Klar and Krupnikov, 2016). For the former, about three in four Independents report leaning towards the Democrat or Republican party, and their voting behavior is not all that different from consistent partisans (Skelley, 2021). For the latter, Klar (2014), finds “Independent” as an identity on its own can be a motivating factor for political engagement (or lack thereof).

These discrepancies between Independents’ identification and attitudes/behaviors fall nicely into Ellemers et al.’s (2020) group-directed threat, *low-commitment* identity condition. Thus, I would expect that the impact of the tone of coverage of the two front-running presidential

candidates on Independents during an election to be in line with weak partisan identifiers: their attitudes would be shifted in the direction of the valence of the coverage. This expectation is only explored (briefly) in Chapter 2. Chapters 3 and 4 focus more narrowly on the differences between partisan social identity attachment and traditional measures of partisanship for actual political group identifiers (Republicans and Democrats). This limitation is discussed in more detail in Chapter 3. That said, I believe that the new measure of partisan identity attachment has the potential give clearer meaning to identifying as “Independent.” In traditional measures, Independents are simply forced to pick a “lean.” The measure proposed in Chapter 3, however, would capture any variation in that lean in relationship to affective and psychological attachment to partisan groups. This could be very useful for future research in the growing scholarship on political Independents in the U.S.

Given the literature reviewed above, I believe there is a strong theoretical argument for the study of partisanship through the framework of SIT in political communication. As Arceneaux and Vander Wielen (2017) nicely summarize, “People’s group attachments shape the intuitions people form” (38). Our biases, strength of attitudes, structures of knowledge and interests are often rooted in our social identities. And that bias strongly influences how we process information. The social identity-approach I’m proposing stakes the claim that it is in accounting for the variation in attachment to and strength of group identities that all these components can be better synthesized, and help scholars better predict the heterogeneous effects of political media on citizens. Attitude strength and psychological information processing help us answer questions like “how?” whereas an identity-focused approach improves our ability to establish “what” the effects will look like to begin with and “why” they occur.

I recognize that studying the impact of our psychological attachment to groups is complex and challenging. The subsequent chapters presented here provide sufficient preliminary evidence to support the theory describe and, I hope, to inspire future research using this framework.

## **Chapter 2 Identity-Based Heterogeneity in Media Effects During U.S. Elections (2000 – 2016)**

In the United States, and around the world, an entire industry has been built to ensure that political candidates get “good press.” The public relations professional and political consultant’s idea of “good press” often applies basic logic to public and media communication strategy: if people hear bad things about you, they’ll think less of you. Applied in politics: if people think less of you, they might not vote for you. There are also concerns about the tone of media coverage among political leaders themselves. For decades, conservative candidates and leadership have been deploying the “liberal media bias” complaint to rally their base when polling numbers drop or media coverage of them or the party is negative (Domke et al., 1999; McChesney, 2004). This strategy has been reinvigorated with President Trump’s frequent public call out of “fake news” to describe media outlets that do not report on him or his policy in a manner in which he likes.

In fact, the 2016 presidential election brought back to the forefront the idea that the tone of coverage of a particular candidate may have a real impact on voters. Bode et al. (2020), for example, find that “the 2016 campaign appears to have been one of the most negative presidential campaigns in recent history” (83) – not just in news coverage but also in social media content and in voter attitudes towards the candidates. They also find that the news media’s “unrelenting” and often negative focus on the investigation into Clinton’s personal email use had a very memorable impact on voters (see also Newport et al., 2016). Did the impact of media in the 2016 election hinge solely on whose coverage was “less negative”? Ultimately, no data can

say with complete certainty what determined voters' choices at the ballot box. But this and other research coming out of the 2016 election indicates that the relationship between tone of media coverage of presidential candidates and voters' attitudes towards those candidates is much more complicated than "good press is good" and "bad press is bad."

It is clear that negative information may matter more than positive. A significant body of work in political communication has examined the importance of valence in understanding people's interest in and reaction to news. Specifically, people seem to have stronger physiological reactions to negative news (Soroka & McAdams, 2015) and are more likely to select negative stories even when they report preference for positive ones (Trussler & Soroka, 2014). The effect of negative news compared to positive news may also vary. Soroka (2006) finds that negative information about the economy had a stronger impact on people's attitudes towards the economy than positive information. This could be driven by heightened awareness of and reaction to a perceived threat, or that negative information is simply "outlying" to our expectations (Lamberson & Soroka, 2018). In the context of an election, negative campaigning tends to be successful at increasing voter engagement and is more memorable than positive messaging; although, attacking your opponent doesn't necessarily win votes (Lau et al., 2007; see also, Phillips et al., 2008). That's not to say that positive coverage doesn't matter at all. There's evidence that positive media coverage of a political party results in more positive attitudes towards that party (Norris et al., 1999) and preferences to vote for that party (Hopmann et al., 2010).

Previous work thus highlights that negative political information is attention grabbing – which is why extensive time and resources are often devoted to channeling negative media attention towards an opponent and away from oneself. Does this increased attention actually

translate to attitudes, though? Kepplinger et al. (1989) study the influence of media sentiment on evaluations of the German Chancellor for over a decade, concluding that shifts in media tone preceded (predicted) shifts in public opinion from months prior. Fournier et al. (2013) successfully connect trends in media coverage to the unexpected surge in popularity of the New Democratic Party during the 2011 Canadian federal election. Wlezien & Soroka (2019) similarly use sentiment analysis of mainstream media coverage during the 2016 U.S. presidential election and commercial polling to explore media's impact on attitudes and find the two are correlated.

Most interestingly, and potentially relevant for viewing these effects through the lens of Social Identity Theory (SIT), there's evidence that the direction of the relationship between negative coverage and attitudes is not always positive. Redlawsk et al. (2010) create an experimental simulation of a political election and find that voters' support for an in-party candidate actually *grew* in the face of negative information – but only to what the authors call an “affective tipping point.” In other words, for most of the exposure the effect of negative information was in the opposing direction of the tone. But when negative information about a candidate reached a particular mass, people were unable (or unwilling) to resist updating their attitudes. This is not only a useful showcase of the heterogeneity in effects, but also suggests a form of biased processing in line with expectations of Ellemers et al. (2002) high-commitment, group-directed threat where identifiers resist and further defend the positive perception of the group (also highly suggestive of motivated reasoning).

There is, in sum, evidence that voter preferences shift in response to changes in the tone of media coverage of political candidates, but the effects are diverse. I believe SIT and political party attachment, as outlined in Chapter 1, can help scholars better interpret and predict this variation in media effects. The tone of media's coverage of a particular party's candidate may

serve as a trigger of group identity-biased processing. Positive press reinforces people's positive perceptions of the in-group, and thus of the self. Negative press, on the other hand, will likely evoke a perception of threat to the group's status or reputation. In this group-directed threat context, people will likely process the negative press in biased ways. Indeed, it may be that strong identifiers are likely to resist, discount or respond defensively to this information in updating (or not updating) attitudes whereas weak identifiers' attitudes are likely to respond in line with the tone of the coverage.

The goal of this chapter is to examine the relationship between media sentiment and partisan attitudes using the SIT framework. I use data collected during the past five presidential election cycles in the U.S. (2000 – 2016) to test my hypotheses. Advancements in automated content analysis in combination with the meticulous tracking of voter attitudes during elections conducted by the American National Elections Studies (ANES) allow me to track fluctuations in media sentiment and the favorability of candidates on a rolling daily basis. Over this time period the ANES data only consistently use the traditional measure of partisanship. Thus, the analysis in this chapter serves as a starting point for testing my theoretical argument. I use existing data and measurement of partisanship as to test the idea: if partisanship operates as psychological attachment to a group, I predict that it will be a meaningful moderator of the effect of changes in media tone on voter attitudes. Specifically:

**Hypothesis 1a:** The effect of negative news will be moderated by partisanship. Further, I expected a “backlash” effect among those exposed to negative news about their in-party.

**Hypothesis 1b:** The variation in effects will be more pronounced for stronger partisans (i.e., stronger attachment to the in-group).



**Hypothesis 2:** The impact of media tone on attitudes about the candidates for Independents (non-identifiers) will be in the direction of the tone. Negative coverage will decrease favorability and positive tone will increase favorability.

I test these hypothesis below as follows. First, I calculate daily fluctuations in positive and negative sentiment in the coverage of presidential candidates during the 2000 – 2016 elections from mainstream national and regional newspapers in the U.S. using the Lexicoder Sentiment Dictionary (Young & Soroka, 2012). Next, I compile the time-series datasets from the ANES for those same presidential elections. The tone of coverage is then used to predict individuals' attitudes towards the front-running candidates over the course of the election (September – election day of the election year). Results indicate that media sentiment matters, although only marginally given strong preexisting attitudes fueled by partisanship. However, I find that my hypotheses are supported overall. The impact of media sentiment on attitudes is indeed moderated by political identities. I believe these results provide at least preliminary evidence of a social identity group dynamic at play in media effects during election contexts. The subsequent chapters more narrowly focus on improving the measure of partisanship in line with SIT theory and testing it on media effects directly.

## **Methodology**

### *Media Corpus*

The database used to calculate sentiment of candidate coverage was drawn from the Lexis Nexis database using the Web Services Kit. The corpus spans from September 1 to election day for each presidential election from 2000 to 2016. Every article – including opinions

and op-eds – that mentions one of major parties or their nominated presidential candidates, published by eighteen different newspapers during the five election periods, make up the starting sample – from national publications like *The New York Times* and *USA Today* to large-scale regional papers like *The LA Times* and *Chicago Sun Times* (see Table 2-1). From this larger corpus, every individual sentence mentioning the name of the parties (Democrat\* and Republican\*) and/or the parties’ front-running candidates (e.g., Gore\* and Bush\* in 2000) was isolated to create a new corpus of “candidate only” sentence-level coverage.

Why focus on sentence-level coverage? Narrowing down allows for a more precise measure of the sentiment of coverage of *the parties and candidates* specifically. For example, a newspaper could produce negative coverage about a particular policy area but highlight positively how a given candidate plans to address it. In this case the article-level negativity is not directed at the candidate and may outweigh what would otherwise be positive reporting on the candidate. There are many, many more scenarios one could imagine where the sentiment of the article *overall* doesn’t necessarily indicate the sentiment of the coverage of the given candidate.

Narrowing to sentence-level coverage does potentially limit the quantity of positive or negative coverage being measured, however. In this case, for example, there could be a sentence about President Bush with no sentiment at all, followed by a sentence such as “He’s down in the polls among women.” The sentence-level analysis would only capture the non-sentiment first sentence and miss the negative coverage that follows. Therefore, this work errs on the side of type II rather than type I errors, favoring precision over validity. Although the results that follow may at times under-estimate the tone of coverage, the sentence-level analysis at least cuts through some of the messiness and more narrowly targets the variable of interest: tone of coverage, specifically of the party and candidate.

Table 2-1: National and regional newspapers, total articles covering U.S. presidential election (2000-2016)

<i>Arizona Republic</i>	4,485
<i>Arkansas Democrat-Gazette</i>	6,673
<i>Atlanta Journal Constitution</i>	10,327
<i>Boston Globe</i>	14,801
<i>Chicago Sun-Times</i>	11,058
<i>Chicago Tribune</i>	19,033
<i>Denver Post</i>	5,341
<i>Houston Chronicle</i>	11,675
<i>LA Times</i>	19,584
<i>Minneapolis Star-Tribune</i>	3,982
<i>New York Times</i>	37,154
<i>Orange County Register</i>	4,077
<i>Philadelphia Inquirer</i>	6,747
<i>Seattle Times</i>	5,912
<i>St. Louis Post-Dispatch</i>	11,377
<i>Tampa Bay Tribune</i>	10,446
<i>USA Today</i>	10,039
<i>Washington Post</i>	33,078

The resulting dataset includes nearly 250,000 sentences about the parties and/or front-running candidates during the past five elections. The sentences were coded for tone using the Lexicoder Sentiment Dictionary (LSD) (Young & Soroka, 2012), by counting the number of positive and negative words, expressed as a proportion of total words in the sentence. The LSD uses a “bag-of-words” approach where it simply counts the presence of positive and negative words based on a pre-determined list of words in each category. Unlike other sentiment dictionaries, the words included in LSD are designed to clearly *distinguish* between negative and positive sentiment (i.e., it has no overlapping terms). It is also worth mentioning the words are generically negative and positive, rather than specific to a domain like politics. It includes, for example, positive words like “cheerfulness,” “optimistic,” and “respect” and negative words like “aggression,” “chaos,” or “anxiety”(Young & Soroka, 2012). Yet again, the resulting measure prioritizes precision. (It is also much more time and cost effective to use such a tool as the LSD over human coding, for example, given the sheer quantity of text in the corpus.)

The final media corpus includes a measurement of the percent positive and negative tone, and net tone, of coverage for each front-running candidate every day during the set time period. Being able to calculate the sentiment of coverage in a way that matches up exactly with the individual date on which the American National Election Studies (ANES) respondents were interviewed allows for a direct testing of the relationship between fluctuations in media sentiment and voter attitudes, on a daily basis.

#### *American National Elections Studies Data*

Using data from the ANES to track voter attitudes has many advantages. First, it is one of the few data collection projects that consistently measures people's feelings about candidates during every election cycle (and includes pre-election measurement). Second, I chose to use the time-series datasets from ANES for this analysis because it distributes interviews over the course of the campaign period; as a result, it captures attitudes leading up to the election, and these attitudes can be matched to over-time changes in the media sentiment corpus. To reiterate, the central objective of this project is to examine if media tone truly influences people's attitudes during elections. Therefore, it's critical to measure media sentiment at time (t-x) where (t) is the date the attitude was measured, as that fluctuates throughout the election.

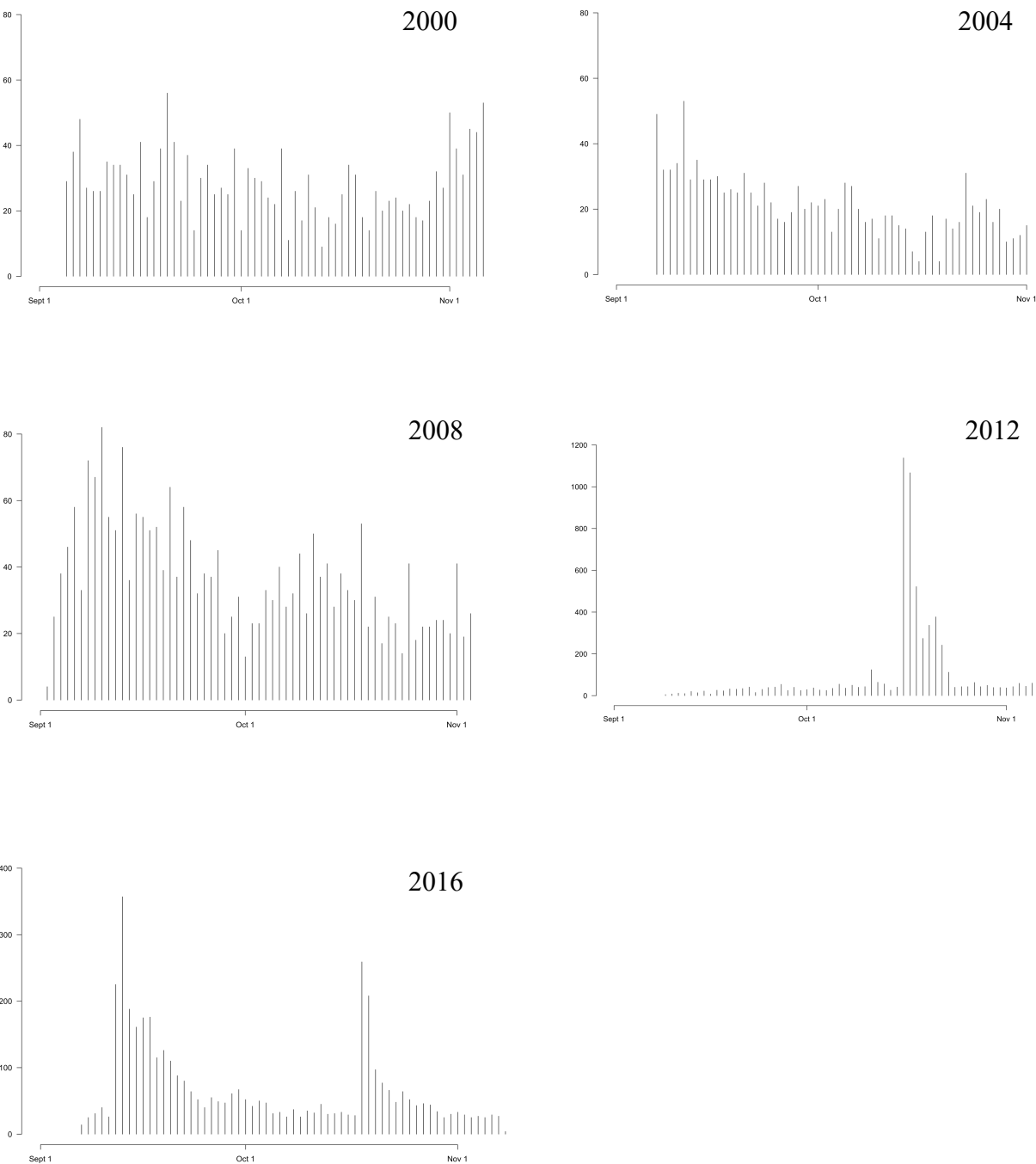
ANES time-series datasets were combined and the measures re-coded for uniformity across the five elections (explained in more detail below). Overall, the ANES uses face-to-face interviewing, and in 2012 and 2016 digital questionnaires were also used. The time-series datasets begin between September 2 and September 9, depending on the year, and run through election day. The number of time-series respondents fluctuates between the five election years used in this analysis (see Table 2-2) and on a daily basis within the pre-election window (Figure 2-1). During the elections 2000 – 2008, daily respondents regularly fluctuated between five or

ten a day to upwards of about 80 per day. In 2012 and 2016, the total number of respondents in the survey significantly increased due to the expansion into internet-based surveying. Note in Figure 2-1 that in 2012, there were more than 1000 respondents collected in mid-October and in 2016, about 300 – 400 were collected at high points in mid-September and again in mid-October. With the exception of these high points, the distribution of respondents every day over the time period is relatively consistent. Overall, there are more than 15,500 total respondents included in the dataset over the five-election period.

*Table 2-2: ANES Time-Series Respondents (2000-2016)*

<i>2000</i>	1,807
<i>2004</i>	1,212
<i>2008</i>	2,322
<i>2012</i>	5,914
<i>2016</i>	4,271
<b><i>Total</i></b>	<b>15,526</b>

Figure 2-1: Daily Distribution of ANES Respondents in Time-Series Surveys, 2000 – 2016



### *Dependent Variable: Voter Attitudes*

The most consistent measure deployed by the ANES over the five-election time period in capturing voter attitudes towards the major presidential parties' candidates is the feeling thermometer. Respondents are asked to rate the current presidential candidates along a scale from 0 – 100, where 0 is the most cold or unfavorable feeling towards the candidate, and 100 is the most warmth or favorability towards the candidate. The scale allows for small fluctuations in attitudes to be captured more accurately than in categorical or Likert-scale measures of attitudes. This variable was measured daily for every respondent in the ANES time-series data from early September up to election day for every election period.

### *Independent Variable: Media Sentiment*

As outlined above, automated content analysis of the media corpus using the LSD allowed for a daily measure of positive, negative and net tone of coverage of the major parties and their nominated presidential candidates for the period of September through election day in each election year (2000 – 2016). The focus of this chapter is to examine what, if any, impact changes in media tone have on voter attitudes. Therefore, the independent variable *media sentiment* used in subsequent analyses is the tone of coverage prior to the date of the respondents' interviews (when the dependent variable, voter attitude, is measured). There is very little prior research indicating a time lag for such a measure – particularly when investigating aggregated trends as opposed to individual-level effects measured in a controlled experiment. I accordingly ran my initial analyses using the following time frames for the independent variable: tone of media one day prior to measurement of attitude, the average tone of 1 – 3 days prior, 2 – 4 days prior, 3 – 5 days prior, 4 – 6 days prior, 5 – 7 days prior, and finally, the average tone for the week prior. There were nearly no effects for the single day prior, but very present effects for

the various multi-day averages and weekly average. This seems reasonable, as any change in media tone only one day prior may be altogether missed by the respondent or potentially too insignificant to have any kind of impact on attitudes. A multi-day change is more indicative of a noticeable trend. Most importantly, there were only marginal differences in the estimated effects across the different combinations of day ranges. Hence, all the models presented in this chapter focus on measures of media tone averaged and lagged the week prior to daily measures of voter attitudes.

#### *Moderator: Political Partisanship*

The main objective of this project is to examine the role of political party identification in understanding and predicting media effects in political contexts. Specifically, I predict in hypothesis 1a that we should expect *different* kinds of effects contingent on the in-group/out-group dynamic at play. Note, I argue that partisanship operationalized as a “social identity attachment” is a critical component of this exploration, but the data used for this chapter are limited in that regard. The ANES data over this extended time period most consistently measures partisanship by asking: “Generally speaking, do you usually think of yourself as a Republican, Democrat, an Independent, or what?” followed by “Would you call yourself a strong [Democrat/Republican] or a not very strong [Democrat/Republican]?”. Independents are asked “Do you think of yourself closer to the Republican Party or the Democratic Party?” The result is a seven-point scale of partisanship (from *strong* to *leaner*) to qualify the “level of attachment” to either of the two parties. I refer to this measure, the traditional and most commonly used measure of partisanship across political science and communication disciplines, as PID throughout this project.



This ANES measure of partisan identity (PID) has been argued to fall short in measuring partisanship as a social identity attachment (see summary in Huddy, Davies & Sandor, 2020). For example, Huddy et al. (2020) highlight that the phrasing “think of yourself” indicates more of a cognitive evaluation, rather than an affective one. Improving on measurement of partisan identity in surveys, and its impact on evaluating media effects, is the primary focus of the subsequent chapters. Thus, I will simply use PID here because it is the only measure available across *all* the elections of study. I will first collapse PID into three categories using the first part of the question (Democrat, Republican and Independent) for the initial analyses, and then use the full seven-point scale for the following analyses. These variables will be used as moderators in examining the impact media tone has on voter attitudes.

### *Control Variables*

The analyses conducted in this chapter test the connection between sentiment of coverage of candidates on voters’ attitudes toward those candidates, accounting for a wealth of controls. On average, the ANES shoots for roughly a nationally representative sample in terms of demographics. That appears to be the case in the sub-sample used in this analysis. Gender and education were simplified into binary variables (male/female, some university/no university attendance). Race was measured categorically as white, black or Hispanic. Ideology (i.e., liberalism/conservatism) was accounted for using a five-point scale and general interest in the presidential campaign was binary (interested/not interested). The comparative simplicity of the coding of control variables reflects an effort to maintain consistency between datasets collected by the ANES every four years spanning 16 total years, where there were considerable variations in how these concepts were measured. These factors are likely highly correlated with the moderators used in the analyses. Hence, the exercise of including them in the models should, at

least, put media's predictive power to the test above and beyond a wealth of pre-existing conditions that may influence attitudes.

There are two additional variables that are included in some models as control variables, and in other models integrated directly into the analysis. First, most of the models presented below control for variation in candidate popularity across years (accounting for any kind of exceptionalism in a given year) by including the election years as a factor variable. The results thus capture the impact of media tone on the within-campaign variation in attitudes, purged of across campaign differences. Second, it is possible that the quantity of media respondents consume may influence the effect it has on their attitudes. The ANES asks respondents how many days per week, on average, they consume news via the internet, television, newspaper or radio. I combined and averaged these measures into a single measure of total news consumption (days per week), where 0 is no news consumption on any medium and 7 is consumption of news every day on at least one of the four mediums. It's unclear, however, if this kind of measure of media exposure does in fact capture media consumption. Instead, it's likely it indicates a respondents' interest in news or politics or the election. Nonetheless, I include *Daily News Consumption* as a control in the models. Then, to examine the possibility that media effects are contingent on media consumption, I model the effects dividing the sample into high and low media consumers.

### *A Model to Test the Hypotheses*

Previous work in both communication and political science has emphasized the role political party identification plays in consuming news and interpreting information. As mentioned above, Redlawsk et al. (2010) find in an experimental setting that negative information presented to strong party identifiers may have the *opposite* effect one might think –

driving *more* support toward the party or candidate. The following analysis puts this finding to the test for the first time in multiple, real election settings. The analysis can be articulated mathematically as follows, where A is voter attitudes, MS is average media sentiment over the week prior to the attitude measured at time (t) and PID is political party identity (representing both the three-category and seven-point iterations):

$$A_t = f(\text{MS}_{(t-1,7)} \times \text{PID})$$

Results of this model are tested below. Note that I ran the models using two different estimators: standard OLS regression and a panel data model that relies on clustered standard errors in order to account for correlated errors across respondents interviewed on the same day. Panel data models are included in Appendix A, Tables A1 and A2. I rely on the simple OLS models below because standard errors differ only marginally – a product of the large number of days on which respondents are interviewed (see Figure 2-1, above).

## Results

### *Impact of Media Sentiment on Voter Attitudes*

Table 2-3 shows estimates from a baseline model in which the Republican party candidate feeling thermometer is regressed on media tone and a set of demographic and election year control variables. Table 2-4 shows the same models for the Democratic party candidate feeling thermometer. I have no strong expectations for these results, but they provide useful baselines with which to compare results in the subsequent models that allow for media effects to vary across partisan groups. Recall that respondents' attitudes are measured at time (t), the date of the interview, and the proportion of positive/negative coverage for each candidate is averaged over the time (t-1) to (t-7).

In Tables 2-3 and 2-4, three different versions of sentiment are explored: Negative and positive separately, ‘net sentiment’ for each candidate, and the difference in ‘net sentiment’ *between* the two candidates. Results in the first column suggest that positive tone is more strongly correlated with attitudes than negative tone, and the relationship is positive (as expected). This pattern holds for evaluations of both Republican and Democratic candidates. The measure of net sentiment (in column 2 of the tables) is positively related to attitudes about Democratic candidates (Table 2-4), but not Republican candidates (Table 2-3). The net difference measures (in column 3) are not significant. It thus appears that variation in the proportion of positive words is more strongly associated with attitudes than variation in negative words when considered separately. This is captured in the net sentiment measure as well, although more apparent for the Democratic than for the Republican party candidate thermometers. As expected, nearly all of the control variables significantly predict attitudes towards the candidate including election year.

As mentioned above, these preliminary models look at patterns of correlations for the entire ANES respondent sample as one group. That is to say, the results describe the overall effect of media tone on attitudes towards the major parties’ candidates for all respondents. It is my hypothesis that the consideration of political party identities should have an influence on the results. That is the focus of subsequent analyses.

Table 2-3: Effect of Tone of Media Coverage on Attitudes Towards Republican Candidates

	Republican Candidate Feeling Thermometer		
Negative Coverage of Republican Cand.	0.637 (0.971)		
Positive Coverage of Republican Cand.	3.740** (1.652)		
Net Sent. of Coverage of Republican Cand.		0.763 (0.660)	
Net Difference in Sentiment			0.364 (0.776)
Female	-0.642 (0.406)	-0.631 (0.406)	-0.630 (0.406)
Black	-8.222*** (0.611)	-8.184*** (0.610)	-8.181*** (0.611)
Hispanic	-2.830*** (0.623)	-2.816*** (0.623)	-2.830*** (0.623)
Independent PID	14.700*** (0.507)	14.708*** (0.507)	14.702*** (0.507)
Republican PID	33.303*** (0.632)	33.306*** (0.632)	33.300*** (0.632)
University Attendance	-2.880*** (0.438)	-2.897*** (0.438)	-2.902*** (0.438)
Ideology (Liberal to Conservative)	6.002*** (0.168)	5.997*** (0.168)	5.997*** (0.168)
Daily News Consumption	0.409*** (0.129)	0.404*** (0.129)	0.405*** (0.129)
Campaign Interest	1.617*** (0.322)	1.613*** (0.322)	1.612*** (0.322)
2004 Election Year (as factor)	-2.469* (1.414)	-0.945 (1.182)	-1.672* (0.999)
2008 Election Year (as factor)	-2.703*** (0.865)	-2.350*** (0.846)	-2.467*** (0.842)
2012 Election Year (as factor)	-8.217*** (0.728)	-8.450*** (0.719)	-8.635*** (0.731)
2016 Election Year (as factor)	-20.123*** (1.159)	-18.864*** (0.966)	-19.379*** (0.837)
Constant	26.477*** (6.764)	39.645*** (0.920)	39.760*** (0.913)
Observations	13,838	13,838	13,838
R <sup>2</sup>	0.450	0.450	0.450

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

Table 2-4: Effect of Tone of Media Coverage on Attitudes Towards Democratic Candidates

	Democratic Candidate Feeling Thermometer		
Negative Coverage of Democratic Cand.	-0.758 (0.973)		
Positive Coverage of Democratic Cand.	6.025*** (1.653)		
Net Sent. of Coverage of Democratic Cand.		2.385*** (0.708)	
Net Difference in Sentiment			-0.519 (0.748)
Female	2.061*** (0.391)	2.070*** (0.391)	2.076*** (0.391)
Black	18.951*** (0.588)	19.004*** (0.587)	19.025*** (0.588)
Hispanic	9.777*** (0.599)	9.776*** (0.599)	9.753*** (0.600)
Independent PID	-18.751*** (0.488)	-18.730*** (0.488)	-18.742*** (0.488)
Republican PID	-34.778*** (0.609)	-34.787*** (0.609)	-34.800*** (0.609)
University Attendance	0.404 (0.422)	0.379 (0.422)	0.362 (0.422)
Ideology (Liberal to Conservative)	-5.886*** (0.162)	-5.888*** (0.162)	-5.890*** (0.163)
Daily News Consumption	0.493*** (0.124)	0.490*** (0.124)	0.493*** (0.124)
Campaign Interest	1.349*** (0.309)	1.347*** (0.310)	1.343*** (0.310)
2004 Election Year (as factor)	-4.356*** (1.267)	-3.201*** (1.176)	-5.466*** (0.966)
2008 Election Year (as factor)	-1.630** (0.818)	-2.023** (0.802)	-2.268*** (0.811)
2012 Election Year (as factor)	-3.009*** (0.750)	-3.436*** (0.729)	-4.168*** (0.703)
2016 Election Year (as factor)	-16.650*** (0.828)	-16.629*** (0.828)	-17.966*** (0.805)
Constant	52.681*** (6.752)	69.003*** (0.880)	69.301*** (0.879)
Observations	13,864	13,864	13,864
R <sup>2</sup>	0.536	0.535	0.535

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

### *Interaction of Media Sentiment and Political Identity*

Recall that the main objective of this project is to consider the possibility that media effects are moderated by political identity. Table 2-5 shows the predictive power of net media sentiment on attitudes about candidates (i.e., predicting average change in attitudes) moderated

by the respondents' own party identification, over the five elections. This analysis, and those following, use *net sentiment* as the independent variable for two reasons. First, as I introduce moderators and continue to increase the complexity of the models, it is more efficient computationally to use only one measure of media sentiment. Second, even though the impact of net sentiment was not significant across all the models above, those models do not examine partisan heterogeneity. Preliminary analyses suggested consistent effects of net sentiment in the context of heterogeneity, however; and no substantive difference from models that include positive and negative sentiment separately.

From the start, it is important to note that Democrats, Independents and Republicans are so far apart in their feelings of warmth towards a particular candidate that fluctuation in the tone of media coverage about a candidate has little overall effect on people's feelings about that candidate. The direct effect of PID on voter attitudes in Table 2-5 has near symmetric effects for evaluations of Republican versus Democratic candidates. The coefficient for Democratic respondents evaluating Republican candidates is -18.21 ( $p < 0.01$ ) and for Republican respondents evaluating Democratic candidates is -23.132 ( $p < 0.01$ ). For in-party evaluations, the coefficients for Republicans and Democrats are 25.336 ( $p < 0.01$ ) and 21.502 ( $p < 0.01$ ), respectively. To be clear: no variation in media sentiment will swing an Independent towards as warm of feelings about the Democratic/Republican candidate as Democrats/Republicans already feel about their own candidate – the threshold is just too high (or low). The important inference here is that partisanship is so overwhelmingly influential on people's attitudes about a candidate that positive or negative coverage of that candidate will fail to *fundamentally* change those attitudes, only slightly sway it.

*Table 2-5: Effect of Net Sentiment of Media Coverage on Attitudes Towards Candidates, Moderated by Partisanship*

	Republican Therm.	Democrat Therm.
Net Sentiment of Rep. Cand. Coverage	0.020 (0.927)	
Net Sentiment of Dem. Cand. Coverage		4.596*** (1.051)
Democrat PID	-18.120*** (0.553)	21.502*** (0.583)
Republican PID	25.336*** (0.611)	-23.132*** (0.651)
Net Sent. Rep. x Dem. PID	4.435*** (1.058)	
Net Sent. Rep. x Rep. PID	-3.406*** (1.139)	
Net Sent. Dem. x Dem. PID		-6.115*** (1.313)
Net Sent. Dem x Rep. PID		0.718 (1.427)
Female	-1.094*** (0.421)	2.626*** (0.406)
Black	-6.702*** (0.630)	17.633*** (0.607)
Hispanic	-2.584*** (0.647)	9.517*** (0.623)
University Attendance	-3.899*** (0.453)	1.421*** (0.437)
Daily News Consumption	0.563*** (0.134)	0.337*** (0.129)
Campaign Interest	1.485*** (0.333)	1.491*** (0.321)
2004 Election Year (as factor)	-2.534** (1.219)	-1.419 (1.216)
2008 Election Year (as factor)	-3.458*** (0.863)	-0.828 (0.818)
2012 Election Year (as factor)	-9.558*** (0.728)	-2.310*** (0.742)
2016 Election Year (as factor)	-20.937*** (0.990)	-14.525*** (0.846)
Constant	56.329*** (0.905)	48.429*** (0.877)
Observations	14,023	14,051
R <sup>2</sup>	0.399	0.490
Residual Std. Error	24.628 (df = 14007)	23.783 (df = 14035)
F Statistic	20.413*** (df = 15; 14007)	899.825*** (df = 15; 14035)

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01



That is not to say that the tone of coverage about a candidate has *no* influence on people's attitudes, nor that this slight sway couldn't have a significant impact, however. It is entirely possible that a swing from neutral on the feeling thermometer (50) to slightly more warmth (55 – 60) may be just enough to influence someone's decision to vote. And regardless of a shift in vote, the extent that there is a shift at all in attitudes helps us better understand media effects in political contexts.

In Table 2-5, the direct effect of net sentiment is only significant in predicting changes in attitudes about the Democratic candidates. Most importantly, however, the results of the moderating variables in Table 2-5 suggest that media tone may be affecting different people in different ways. Note that for the interaction term (net sentiment x PID), the sign of the coefficient – which is significant for both Republicans and Democrats – is negative for respondents evaluating their *own party's candidate*. There clearly is an interplay of media tone and partisan group affiliation, as the literature suggested, and supporting my hypotheses.

These results are more easily interpreted in Figures 2-2 and 2-3, which illustrate the estimated effect of media negativity on thermometer scores, conditional on party identification for Republican respondents (in red), Democratic respondents (in blue) and Independent respondents (in grey). When the tone of media coverage of a respondent's own party's candidate is more negative, they report feeling *more warmth* towards their candidate, rather than less. This is true for both Democrats (in Figure 2-3) and Republicans (in Figure 2-2). Conversely, when the tone of media coverage of the *opposing party's* candidate is negative, respondent attitudes change in the same direction as coverage (i.e., the coefficient is positive, rather than negative). In this instance attitudes are updated as we would traditionally expect – more negative tone leads to less warmth towards the candidate. Thus, hypothesis 1a is supported.

Note that the relationship between media tone and attitudes for Independents evaluating Democratic candidates follows the direction of the media tone as well, although media seem to have no impact on Independents evaluating Republican candidates (partially supporting hypothesis 2). See this illustrated in Figure 2-2 where more negative the coverage of the Republican candidate is correlated with increasing feelings of warmth for Republican respondents. The same is true for Democrats evaluating their own candidate (Figure 2-3), however with slightly less magnitude.

*Figure 2-2: The Average Impact of Negative Press on Attitudes for Republican Candidates*

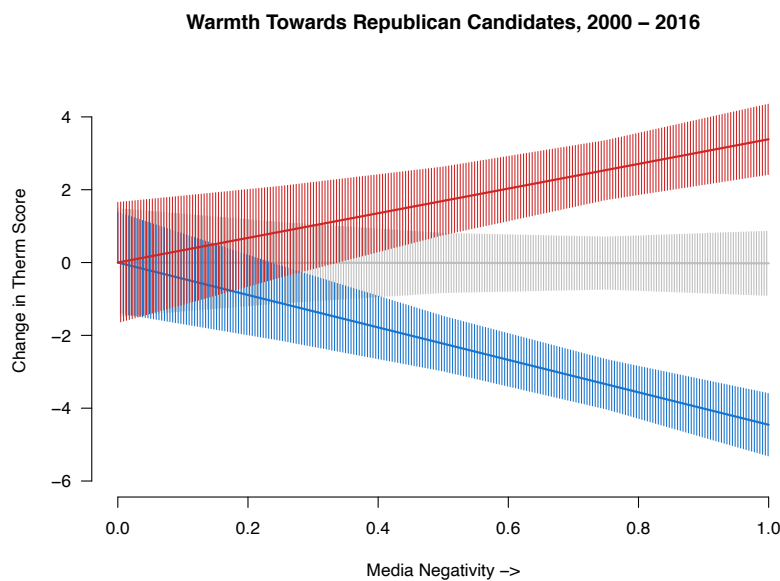
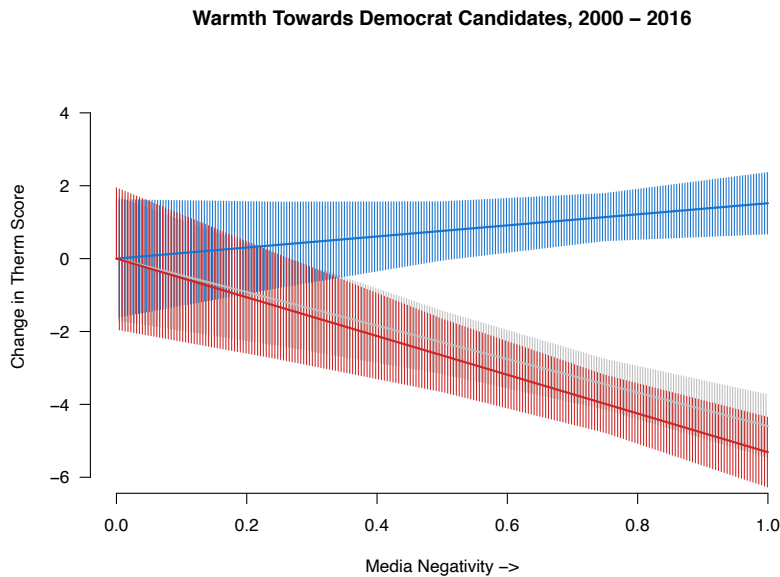


Figure 2-3: *The Average Impact of Negative Press on Attitudes for Democrat Candidates*

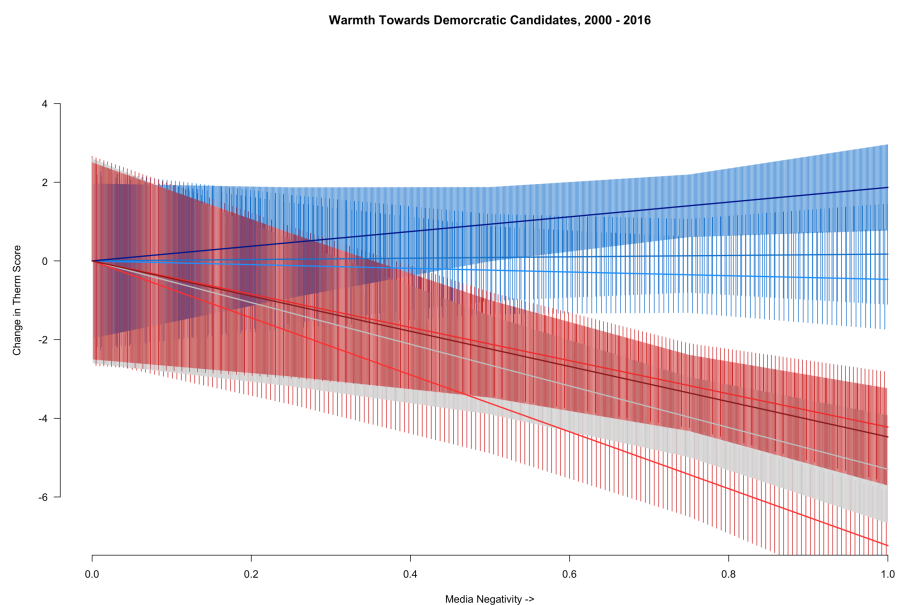


When respondents are separated by their party identification, the media effects observed shift rather significantly. In Tables 2-3 and 2-4 we see that the relationship between media sentiment and attitudes is positive and may in fact be mostly driven by positive tone specifically. The results in Table 2-5, however, demonstrate that analyzing media effects from the perspective of group identities alters the direction and magnitude of media effects in meaningful ways. This is a promising result to have drawn from real attitudes captured during past presidential elections (and especially given the limitations of the data), which will be addressed further in the discussion and chapters that follow.

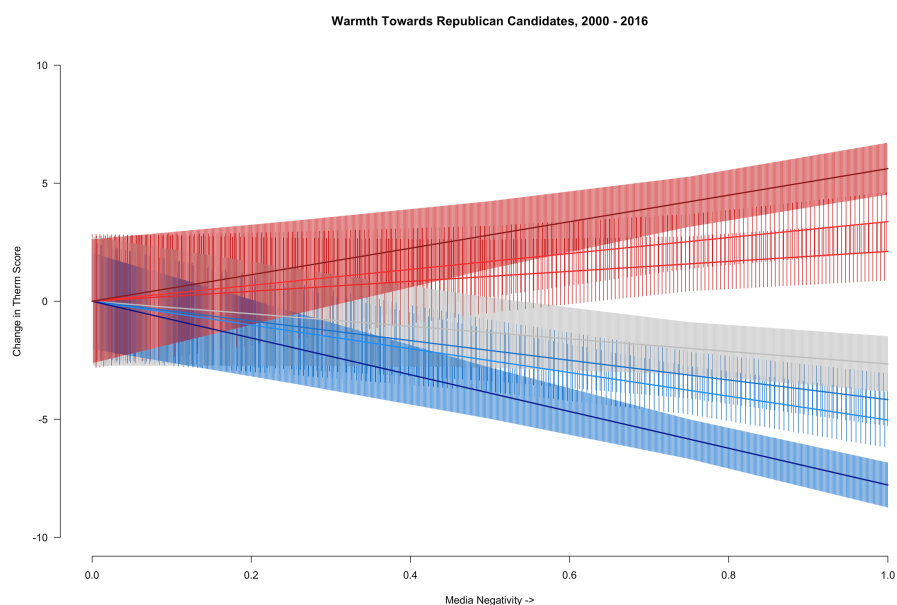
I argue that it may also be the case that the *degree* to which one identifies with a political party matters for media effects. I consequently utilize the full seven-point PID scale to re-estimate the models above. The results are illustrated in Figure 2-4 and Figure 2-5; for the sake of parsimony, the full results are included in Appendix A, Table A3. As above, in Figures 2-4 and 2-5 Republican respondents are represented in red, Democrats are represented in blue, and Independents are represented in grey. The density of the three red and three blue lines corresponds with the “strength” of attachment to that party (denser is more strongly attached).

In both Figures 2-4 and 2-5, the strongest in-party identifiers are most influenced by media tone when evaluating their own party’s candidate. The direction of the results is as we have already seen, in that the more negative the tone of media coverage of one’s own party’s candidate, the more one feels *warmth* towards that candidate. Furthermore, the strongest in-party identifiers report the most increase in positive attitudes towards the in-party candidate as coverage of that candidate is more negative. This is an initial indication that the degree to which someone identifies with a party group (represented as “strength” here) does matter in terms of the magnitude of the impact of media on attitudes. Hypothesis 1b is supported.

*Figure 2-5: The Average Impact of Negative Press on Attitudes for Democrat Candidates, Seven-point Partisan Measure*



*Figure 2-4: The Average Impact of Negative Press on Attitudes for Republican Candidates, Seven-point Partisan Measure*



It is worth noting that the moderated effects may be slightly stronger for Republican respondents than for Democrat respondents. For Republicans, as the tone of media coverage of

their party's candidate becomes more negative, the fluctuation in the feeling thermometer on average can increase up to about five points. Going from a 75% warm feeling to 80% could be potentially meaningful. On the other hand, even as media coverage of their own party's candidate grows negative, the effect on Democrats' attitudes is slimmer – increasing their feelings of warmth by about one or two points (although statistically significant). The constraints of the data in this chapter do not allow for us to expand in this idea further, but it serves as a potential starting point to hypothesize that the “diverging” of effects may not just be in-party vs. out, but also between the two parties as well.

To what extent are the results driven by any single election? Running each election on its own leads to a precipitous drop in sample size, so I instead opt for a different approach: I run the models in Table 2-5 removing one year at a time in order to assess whether the results are driven by one particular election year. These analyses are in Table 2-6 (Republican candidates) and Table 2-7 (Democrat candidates). The first columns of the tables are the results of the model removing the data from election year 2000, in column two data from 2004 is removed, in column three 2008 is removed, and so on. Note first that all the interaction terms both for Democrat respondents and Republican respondents are replicated – as in the sign is positive for out-party evaluations and negative for in-party evaluations. For attitudes towards Republican candidates, it appears that no removal of any of the five election years impact the results. The removal of the 2000 election is the only case where the interaction coefficient loses some significance. Overall, the robustness of the model holds up to the exclusion of any particular election.

Table 2-6: Effect of Net Sentiment of Media Coverage on Attitudes Towards Republican Candidates, Moderated by Partisanship, Years Removed

	Dependent variable:				
	Republican Candidate Feeling Thermometer				
	(1)	(2)	(3)	(4)	(5)
Net Sentiment of Rep. Cand. Coverage	5.119*** (1.113)	9.925*** (1.063)	7.953*** (1.138)	7.196*** (1.119)	0.594 (1.380)
Democrat PID	-18.078*** (0.782)	-16.879*** (0.682)	-17.838*** (0.792)	-14.717*** (0.903)	-16.153*** (0.688)
Republican PID	25.978*** (0.894)	24.359*** (0.765)	25.335*** (0.870)	23.985*** (0.998)	24.037*** (0.785)
Female	-1.664*** (0.461)	-1.276*** (0.443)	-1.494*** (0.473)	-1.373** (0.570)	-0.088 (0.475)
Black	-6.198*** (0.683)	-6.504*** (0.660)	-6.816*** (0.732)	-5.761*** (0.868)	-5.985*** (0.671)
Hispanic	-2.897*** (0.685)	-2.974*** (0.665)	-5.151*** (0.739)	-4.918*** (0.933)	-1.460** (0.702)
University Attendance	-4.588*** (0.496)	-4.259*** (0.477)	-5.400*** (0.513)	-6.796*** (0.616)	-2.715*** (0.497)
Daily News Consumption	-1.246*** (0.125)	-0.774*** (0.123)	-0.955*** (0.125)	-1.745*** (0.141)	0.679*** (0.157)
Campaign Interest	3.441*** (0.358)	2.689*** (0.345)	2.661*** (0.370)	2.716*** (0.435)	1.110*** (0.368)
Net Sent. Rep. x Dem. PID	4.670*** (1.509)	6.156*** (1.430)	6.390*** (1.560)	7.669*** (1.523)	8.627*** (1.858)
Net Sent. Rep. x Rep. PID	-2.247 (1.670)	-3.453** (1.564)	-3.966** (1.661)	-4.870*** (1.650)	-6.310*** (2.113)
Constant	51.693*** (0.835)	52.360*** (0.764)	53.755*** (0.849)	57.800*** (0.998)	48.709*** (0.815)
Observations	12,494	13,060	11,932	8,529	10,077
R <sup>2</sup>	0.375	0.365	0.384	0.356	0.372
Adjusted R <sup>2</sup>	0.374	0.364	0.384	0.355	0.372
Residual Std. Error	25.483 (df = 12482)	25.080 (df = 13048)	25.593 (df = 11920)	25.992 (df = 8517)	23.607 (df = 10065)
F Statistic	680.452*** (df = 11; 12482)	681.207*** (df = 11; 13048)	676.089*** (df = 11; 11920)	427.209*** (df = 11; 8517)	542.707*** (df = 11; 10065)

Note:

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

Table 2-7: Effect of Net Sentiment of Media Coverage on Attitudes Towards Democratic Candidates, Moderated by Partisanship, Years Removed

	Dependent variable:				
	Democratic Candidate Feeling Thermometer				
	(1)	(2)	(3)	(4)	(5)
Net Sentiment of Dem. Cand. Coverage	8.951*** (1.155)	16.011*** (1.278)	7.886*** (1.194)	9.688*** (1.128)	4.234*** (1.188)
Democrat PID	22.205*** (0.670)	21.230*** (0.598)	25.052*** (0.695)	20.945*** (0.743)	19.746*** (0.614)
Republican PID	-25.834*** (0.761)	-22.887*** (0.673)	-22.965*** (0.760)	-20.799*** (0.820)	-23.764*** (0.696)
Female	2.227*** (0.440)	2.307*** (0.428)	2.307*** (0.451)	2.709*** (0.530)	2.632*** (0.469)
Black	19.687*** (0.651)	19.204*** (0.635)	17.938*** (0.697)	15.276*** (0.806)	17.931*** (0.661)
Hispanic	10.094*** (0.654)	9.808*** (0.640)	9.413*** (0.703)	8.317*** (0.865)	8.380*** (0.692)
University Attendance	0.891* (0.473)	1.012** (0.460)	0.696 (0.489)	0.529 (0.572)	1.273*** (0.490)
Daily News Consumption	-1.399*** (0.116)	-0.976*** (0.116)	-1.248*** (0.116)	-1.411*** (0.129)	0.273* (0.154)
Campaign Interest	3.143*** (0.341)	2.336*** (0.332)	2.477*** (0.353)	3.954*** (0.404)	1.011*** (0.362)
Net Sent. Dem. x Dem. PID	-4.933*** (1.614)	-13.580*** (1.735)	-1.258 (1.680)	-6.132*** (1.575)	-2.649 (1.652)
Net Sent. Dem x Rep. PID	-4.434** (1.774)	3.133 (1.944)	0.124 (1.783)	0.904 (1.698)	2.438 (1.799)
Constant	48.312*** (0.763)	48.663*** (0.712)	47.730*** (0.785)	47.141*** (0.890)	48.893*** (0.771)
Observations	12,511	13,101	11,957	8,529	10,106
R <sup>2</sup>	0.490	0.485	0.477	0.437	0.459
Adjusted R <sup>2</sup>	0.489	0.484	0.477	0.436	0.458
Residual Std. Error	24.343 (df = 12499)	24.213 (df = 13089)	24.414 (df = 11945)	24.139 (df = 8517)	23.309 (df = 10094)
F Statistic	1,091.013*** (df = 11; 12499)	1,118.687*** (df = 11; 13089)	990.906*** (df = 11; 11945)	600.810*** (df = 11; 8517)	777.270*** (df = 11; 10094)

Note:

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01



The results of re-running the model for evaluations of Democratic candidates are a bit more complex, but overall yield a replication of the initial results (see Table 2-7). For Democratic respondents evaluating their own candidate, all the interaction coefficients are negative. However, the coefficients lose significance when the 2008 and 2016 elections are removed. It is possible that something about the nature of coverage in those particular elections (President Obama's first run in 2008 and Clinton's run in 2016) may have had a particularly strong impact on the relationship between media and attitudes towards the candidates. But overall, again, the sign is correct and most of the models hold significance. For Republicans evaluating Democratic candidates, the positive sign of the coefficient is replicated across all elections except when 2000 is removed, although none reach significance. When the 2000 election is removed, the coefficient for Republican respondents is *negative* and significant. It is possible, again, that there is something unique about the media coverage and/or Republicans evaluating the Democratic candidate (Al Gore) in 2000. The most important takeaway here, though, is that the in-party evaluations generally withstand this test.

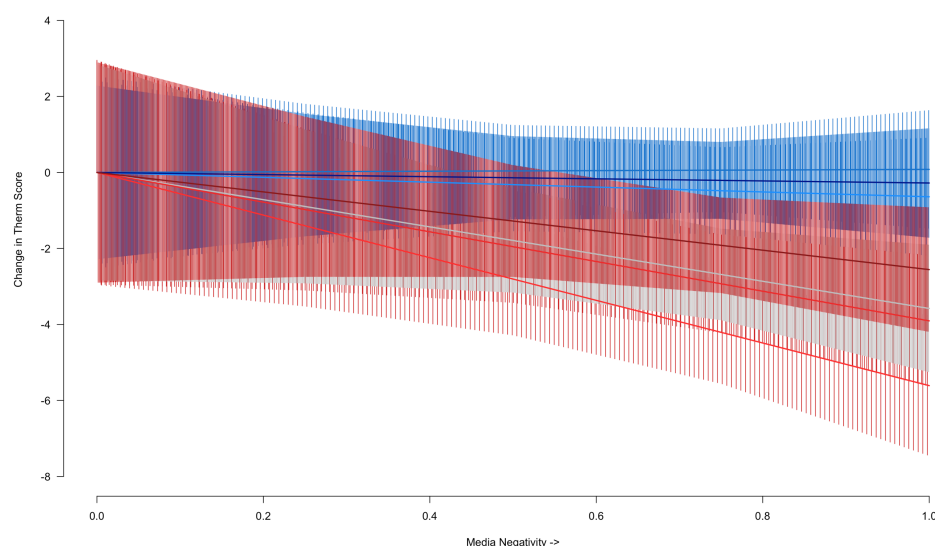
### *The Impact of Media Consumption*

Results thus far have suggested that (a) changes in the sentiment of coverage of presidential candidates does, in fact, predict changes in voter attitudes above and beyond a wealth of control variables (even though the impact is small) and (b) that relationship is greatly influenced by the respondents' partisan identities. If it were the case that *media* is truly the driver of these results, one might also predict that the effects above will be more evident for those respondents who consume more media (or for those with more interest in news/politics). This is the object of the final analysis, the results of which are illustrated in Figures 2-6 through 2-9 below (and Appendix A, Tables A4 and A5). Using the *Daily News Consumption* variable, the

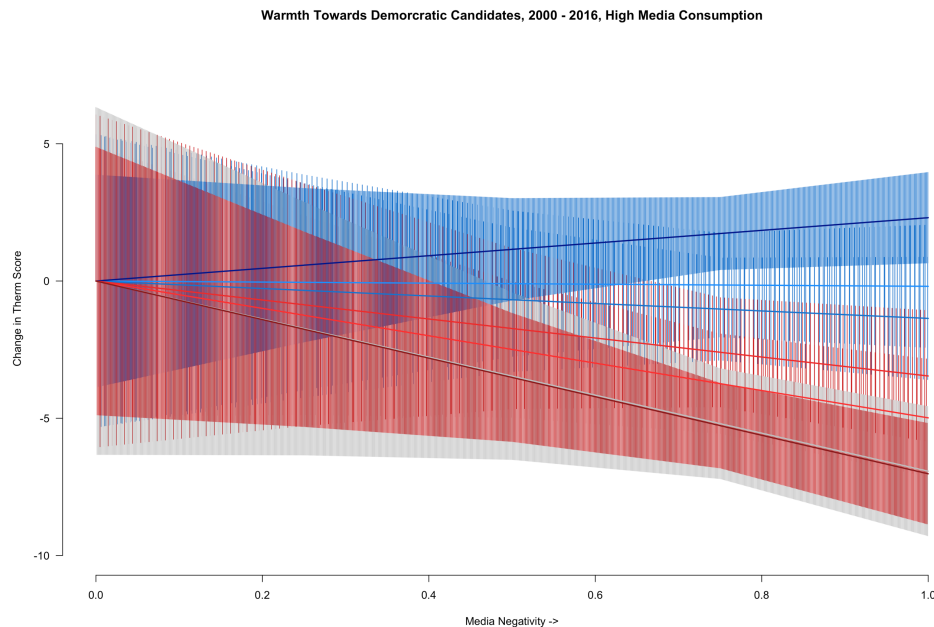
respondents are split into two groups: high media consumers and low media consumers. High media consumers are those who consume some kind of news 5 – 7 days a week and low consumers are those who consume some kind of news 0 – 4 days a week. The models are run separately for these groups, rather than including it as an additional moderator, in order to avoid too much collinearity from a three-way interaction.

For attitudes toward the Democratic candidates, the results are in line with expectations. The attitudes of the low media consumption respondents seem to be less affected by changes in the tone of media coverage than high media consumers. Strong party identifiers who are also high consumers of media replicate the results above (see Figure 2-7) – as media coverage becomes more negative, strong, high-consumption Democrats report increased feelings of *warmth* towards their own candidate compared to strong, low-consumption Democrats (See Figure 2-6). The results are even more pronounced for Republican respondents, where the impact of negative coverage of Democratic candidates leading to more negative feelings about that candidate is stronger for high media consuming Republicans, compared to low.

*Figure 2-6: The Average Impact of Negative Press on Attitudes for Democrat Candidates, Low Media Consumers*



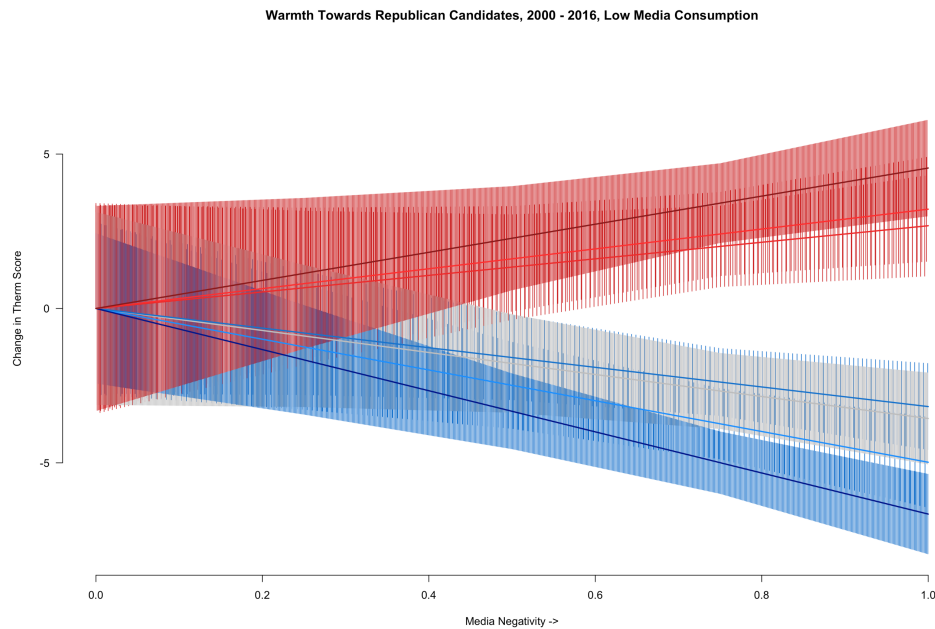
*Figure 2-7: The Average Impact of Negative Press on Attitudes for Democrat Candidates, High Media Consumers*



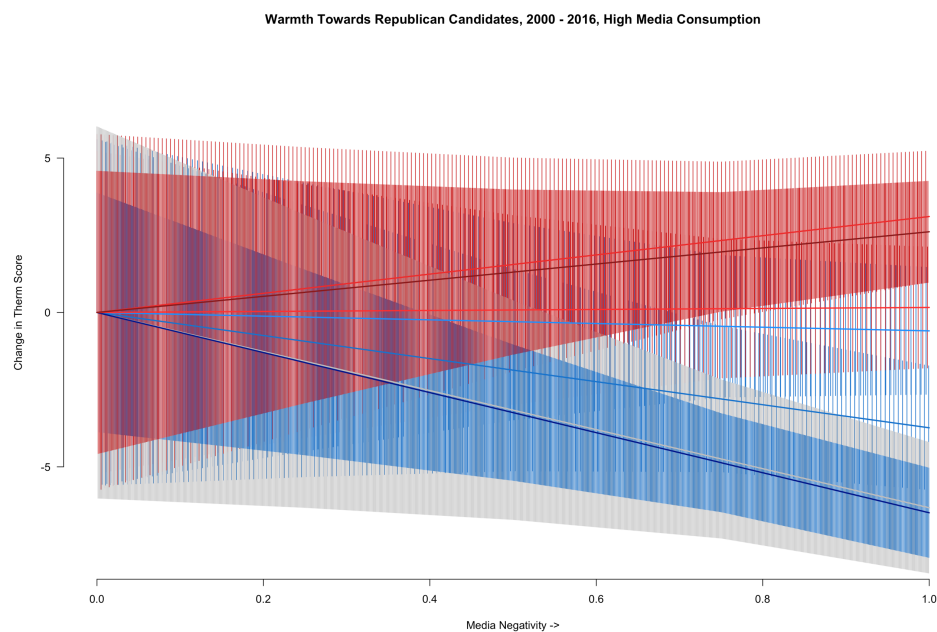
The results for evaluations of Republican candidates are much less moderated by low or high media consumption. For both groups of respondents, the divergent impact of media tone on voter attitudes holds. Figure 2-8 shows low media consumption respondents, and it's very clear that there is a positive relationship between media sentiment and the attitudes of Democratic respondents and a negative relationship between Republican respondents' evaluations and negative press of their own party's candidate. For high media consumers the overall result is the same, but surprisingly a little less pronounced for the strongest Republican identifiers (Figure 2-9). Regardless of how much news is consumed, Republican respondents clearly feel more favorable towards their own party's candidate as media coverage is more negative of that candidate. This could potentially help us understand why there is a difference in magnitude of the effect between Democrats and Republicans – for Democrats it may be contingent on how

much news they actually consume, whereas Republicans' reactions are consistent regardless of the quantity of news they consume.

*Figure 2-8: The Average Impact of Negative Press on Attitudes for Republican Candidates, Low Media Consumers*



*Figure 2-9: The Average Impact of Negative Press on Attitudes for Republican Candidates, High Media Consumers*



In sum, in dividing respondents into high and low media consumption groups suggests that the amount of news consumed might matter, in that more consumption seems to amplify the effects, for Democrats at least. For evaluations of Republican candidates, however, media consumption does not appear to influence the magnitude of the effect. It's possible that there are simply confounding effects between the measure of media consumption and strength of partisanship. This addressed further in the discussion at the end of this chapter.

### *Independents*

Regardless of whether Independents are attached to that political term as a “group” or not, the front-running presidential candidates (and their media coverage) during the 2000 through 2016 elections considered here did not identify as Independent. For Independent respondents, then, then “in-group” would be whatever party they *lean* towards while the “out-group” would be whatever party they lean away from – or, perhaps, both parties. In the analyses above, self-identified “leaners” were included as such in the Democratic and Republican categories. Thus, Independents in this case are only those who did not self-identify as “leaning” (represented in grey in the graphs). In support of hypothesis 2, the results consistently show a positive relationship between media sentiment and changes in Independent respondents’ attitudes. That is, they update their attitudes in line with the direction of media tone. The only instance where this is not the case is illustrated in Figure 2-2 (Table 2-5), where I examined the impact of tone on attitudes using partisanship as a categorical variable. Independents appear to be very little affected by the tone of coverage of Republican candidates. In all subsequent analyses, the relationship is positive. There’s not much to be gleaned from this data regarding the nature of Independents. However, the fact that Independents respond *in contrast* to in-group partisans’ evaluations of their candidates is in line with my expectations.

## Discussion

Although the effect of media tone on candidate evaluations may be relatively small, there is *some* movement while controlling for a wealth of other variables, such as demographics, interest in the campaign and individual election years. And strikingly, the shift in attitudes may be negatively associated with media tone, contingent on partisan identification. As media coverage is more negative, in-group respondents evaluated their own candidate more favorably, while out-party evaluations were updated in the direction of the tone of coverage. These results appear to be even more pronounced for Democrats who are high news consumers, yet the interaction effect appears to hold for Republican identifiers regardless of the amount of news they consume. While I do not have further data to explore this particularity in the results, there are possible explanations worth exploring in future work. For example, not all information comes through media, of course. Perhaps trends in tone of coverage are also a reflection of the general “tone” of the campaigns or public opinion, reaching people conversationally. What looks like responsiveness to media here may, in some instances, be responsiveness to broader sentiment. Thus, the effects are present even for Republicans who are not high consumers of traditional news media because they get the information in other mediated ways. The results could also be affected by asymmetry in trust of media, where Republicans have continued to grow in distrusting media over time (compared to Democrats, who have increased trust in the past decade or so). It may simply not be useful, then, to separate Republicans into high and low consumption categories when considering the impact of exposure of negative information about the in-party candidate given the universal distrust of the information.

Regardless, it is clear that variation in tone of media matters and that partisans respond to that information in different ways. It is also encouraging that the results are mostly robust to the

exclusion of any single election year. Thus, the evidence supports the hypotheses that (a) the effects of media coverage tone on attitudes are heterogeneous, (b) those effects are moderated by partisanship and (c) they grow in potency as strength in identification increases. As outlined in Chapter 1, if partisanship is operationalized as a group identity, then a presidential election would be an environment of high identity threat. Either your group has the position of power and you are working to maintain it, or your group has the opportunity to take that power away from the opposing group. In this context, and in line with SIT, we predict that negative information about the in-group or the representative of the in-group (the current President/contending presidential candidate) will inspire protective instincts to defend the group and/or reject threatening information. The data presented here shows that ANES respondents evaluated their own candidates more favorably when that candidate's coverage was more negative, fitting within this framework.

Unfortunately, this data has some significant limitations. First, "tone" of coverage was limited to mainstream national and regional newspapers. Television coverage, more partisan-focused media and social media content would likely expand the quantity of sentiment I would be able to track over the campaign period. Second, the data does not directly measure exposure of election coverage for the individual respondents. The results are based on aggregate trends. Finally, the only measure of partisanship that was consistent across the five elections in the ANES time-series data was the traditional measure of PID. Although its seven-point variation proved to be a useful moderator, I argue that it falls short in distinguishing partisans' *strength of psychological attachment* to political parties. Thus, the focus of the next chapter is to review existing literature on the measure of social identity attachment and improve upon PID. The fact that there are significant and hypothesis-proving results despite these limitations is promising,

though. The following chapters will attempt to fill in the gaps of these limitations by examining the nature of partisan social identity measurement as it relates to predicting media effects more directly by running survey experiments on partisans during the 2020 presidential election.



### **Chapter 3 Measuring Partisan Social Identity**

The measurement of psychological attachment to a group, grounded in the theoretical framework of Tajfel (1978)'s Social Identity Theory (SIT), has been deeply and extensively examined in work in psychology and is growing in political science. Social identity is the psychological process by which people define themselves in relation to social groups, where one works to maintain a positive perception of the “in-group” compared to an “out-group” in a way that shapes that person's thoughts, emotions and behaviors (Tajfel, 1978; Tajfel & Turner, 1979). Measuring this phenomenon has been a priority for decades, and past work has shown it to be an important predictor (or mediator/moderator) of a range of outcomes, such as, job satisfaction, consumer behaviors, intergroup conflict, and emotions.

Approaches to measurement in the literature have taken many shapes and forms. Indeed, there have already been several extensive theoretical reviews of the multiple dimensions of social/collective identity (e.g., Sellers et al., 1998; Jackson, 2002; Ashmore et al., 2004; Leach et al., 2008). There has also been rigorous methodological testing of different indices and explorations of their predictive power (e.g., Heere and James, 2007; Bankert et al., 2017). Some measures of social identity are rooted in more universal underpinnings of SIT, designed to be applied to any *type of group* attachment (e.g., Brown and Williams, 1984; Mael and Tetrick, 1992; Kashima 2000; Cameron, 2004). Others have been designed with a specific group in mind and tailored to the unique experience of that kind of group affiliation, such as identifying as an athlete (Martin et al., 1997), as African American (Sellers et al., 1998), as American (Schwartz et al., 2012; Vinney et al., 2019) or as a “fan” of something (Vinney et al., 2019), to name a few.

When it comes to the focus of this project – political party social identity attachment in the U.S. – most of the work has adopted measures from the former approach (universal indices) rather than theorizing the concept via experiences unique to political partisanship. The most current applications, for example, apply Mael and Tetrick’s (1992) Identifying with a Psychological Group or Organization (IDPG) ten-item scale to partisanship directly (e.g., Greene, 2004) or then abbreviate it into a four-item scale (e.g., Huddy et al., 2015). Kelly (1988) also adapted the qualitative work done by Brown and Williams (1984) into a ten-item scale of political party group attachment, which she subsequently truncated to five items.

The sheer quantity of work in this area in psychology points to its potential importance and relevance in understanding how humans think and behave. Political science scholarship on partisanship has grown in this area as well, and, as will be discussed in further detail below, has already presented initial evidence that social identity attachment to political parties is (a) distinct from ideological beliefs or traditional measures of strength of partisanship and (b) is often a stronger predictor of political behavior (e.g., Huddy et al., 2015; Bankert et al., 2017).

It is my hypothesis that social identity attachment measures of partisanship are a worthy exploration for research of political communication effects. Much communication scholarship finds political partisanship strength, as traditionally measured, to be an impactful moderator of media effects. I believe that measuring partisanship as a *group identity attachment* could lead to additional insight into the depth and nature of this moderation, and perhaps help researchers better understand heterogeneity in people’s processing of and reactions to media messages.

The sheer quantity of work in this area has led to a lot of messiness in methodology and measurement, however. While I have identified two patterns of approaches generally – a theory-driven universal indices approach and a specific-to-group experiences approach – there are many

cases of complex overlapping ideas and arbitrary decision making that make it challenging to know what the *right* measure or theory(ies) are. The objective of this chapter is therefore to (1) sort through some of these complexities and (2) offer a more simplified approach in adapting SIT to the measurement of partisanship. I believe this is a necessary precursor to exploring partisanship as social identity in media effects.

To be clear, I will not be simply replicating that which has already been done. I start with a much broader sample of survey questions, focusing on the empirical performance of those measures rather than re-theorizing existing work. And I explore the extent to which these different theoretical constructs are indeed different empirically in the context of American partisan social identity. My work is motivated by observation, not criticism. The choices that previous scholar have made are clearly dependent on the scope and outcome of interest of individual projects. In that vein, the choices I make in this chapter are constructed to both respect previous work and move that work towards the easy application of partisan social identity measurement in survey research.

Note that I do not describe in detail the entire literature on the measurement of social identity here. In part, I have selected projects that explore the existing literature and then attempt to build on that work. I also have selected research that I believe exemplify the breadth and variety of existing work. This strategy is applied to my selection of the survey questions as well, given the repetitive nature of the various applications of these measures. I begin with a review of the *universal* measures of social identity. Then, I turn to measures that are designed for *specific* types of group attachment and conclude with a review of the rather limited application of SIT to measurement of partisan attachment in the U.S. My subsequent analysis focuses on the first wave of a two-wave survey where I fielded 37 different questions measuring about 13 theoretical

concepts of social identity attachment. Even as much theoretical work argues for the multidimensionality of social identity, the data suggest that these dimensions are highly correlated. I accordingly proceed to make recommendations for ten- and four-item indices that can efficiently measure partisan social identity in time- and space-limited survey research.

### **“Universal” Measures of Group Identity Attachment**

Many scholars have developed social identity attachment measures rooted in the original ideas of SIT. The shared assumptions of this work are (a) SIT is a multi-dimensional concept, thus requiring a multi-dimensional measure, (b) those dimensions are universal regardless of the specific group that is being measured and (c) those distinct dimensions matter in predicting various outcomes. While some of these measures were developed via one particular kind of group, such as attachment to an employer or university, the group functions more as a *showcase* of the measure. These kinds of measures are essentially “plug-and-play” by changing a single word in a survey question. For example, “Being a *Michigan Wolverine* is important to me” can easily become “Being a *Republican* is important to me.”

Academic attention to the measurement of social group attachment took off in the 1980’s and 1990’s. Many of the existing indices can be traced back to work done by Brown & Williams (1984), Mael & Tetrick (1992) and Luhtanen & Crocker (1992). Brown & Williams (1984) conduct a qualitative analysis using semi-structured interviews with a group of factory bakers in southern England. There had been recent unrest and conflict at the factory, and the authors were investigating the impact of employees’ emotional/collective attachment to their professional identity and factory “sub-groups” in terms of group differentiation. While they find strong evidence that perceptions of group differentiation predicted conflict, they pointedly observed: “An important objective for further work here, we believe, will be to develop a reliable multi-

item scale of group identification which is short and simple enough to be administered in a variety of research contexts...” (561). This project went on to inform one of the few applications of social identity theory to partisanship by Kelly (1988), which will be discussed in further detail below.

Mael and Tetrick (1992) respond to Brown and Williams’ call with the ten-item Identifying with a Psychological Group or organization (IDPG) measure. The measure was initially tested on student attachment to university identity (1988) and subsequently refined as a measure of employee attachment to their employing organization (1992). IDPG is defined in two parts: first, the perception of shared experiences with a focal group and second, shared characteristics among the group’s members. Those two theoretical components thus shape the measure. *Shared experiences* are “the perception that one shares the experiences, successes and failures of the focal organization, and that these successes and failures apply to and reflect upon the self just as they reflect upon the organization” (816). *Shared characteristics* are “the perception that one shares the attributes and characteristics of prototypical group members” (816).

The questions used in Mael and Tetrick’s work are designed to attend to the measurement of both cognitive and affective group attachment. The questions can be traced to different theoretical components of SIT, such as “feeling of oneness,” “perception of shared prototypical characteristics, virtues and flaws,” “vicariously partake in accomplishments beyond individual powers,” and so on (Mael & Tetrick, 1992, 814). The ten questions were then analyzed using factor analysis with six of the items falling onto the shared experiences dimension and four grouping as shared characteristics.

Luhtanen & Crocker's (1992) work, widely used throughout psychology research, is more focused on collective identity in terms of its impact on one's self-esteem (a sub-category of general self-esteem, if you will). The objective was not designed to measure the extent of one's strength of attachment to a group as much as how one feels about such attachment in terms of positive or negative self-conceptualization. Similar to the work above, Luhtanen and Crocker focus on several key theoretical dimensions and design questions worded to capture such dimensions: (1) *evaluation of the membership*, (2) *private regard*, (3) *public regard* and (4) *identity definition*. Many of the questions used to construct Luhtanen & Crocker's (1992) Collective Self-Esteem Scale are used in the other social identity attachment measures reviewed here. Note that even as their measure does not focus on quantifying the degree of identification, then, questions from the Collective Self-Esteem Scale have informed past work on social identity and they are considered in the forthcoming analyses accordingly.

The universal theory-driven measurement construction used by Mael & Tetrick (1992) and Luhtanen & Crocker (1992) is a method that continues to be repeated over time. Much effort has been devoted to describing the theoretical dimensions of SIT and then converting those ideas into survey or interview questions. This work frequently uses constrained factor analysis to test the validity of the components based on the authors' different conceptions of the relevant subcategories. It is often argued that different subcategories or concepts have the potential to predict meaningful variations in outcomes.

Kashima et al. (2000) nevertheless argue that despite the wide consensus on the multi-dimensionality of social group identification, there is a lack of investigation into the relationship between these components and other variables. These authors focus on distinguishing between cognitive and affective components of social identity and hypothesize that each component

predicts different outcomes when it comes to group threat. Kashima et al. (2000)'s work mostly builds on Spears et al. (1997) which focuses on group differentiation (like Brown & Williams, 1984) and perceived group threat. The affective component, *group identification* is an “affective-evaluative reaction to one's group membership” (98) and the cognitive component, *self-typicality*, is “perceived similarity between the self and in-group” (98). To test these hypotheses, Kashima et al. study student identification with a university, using both novel survey items and survey items drawn from Spears et al. (1997) and Brown & Williams (1984). They find that most items load on two factors, corresponding to group identification and self-typicality, and initial analyses indicate the two components are distinct.

Jackson (2002) does an even deeper dive into the theory of SIT. Similar to work above, the study “...investigates the multidimensional nature of group identity and how different dimensions are uniquely related to in-group and out-group evaluations, intergroup bias and perceived intergroup conflict” (11). Jackson notes that the original definition of SIT included three dimensions: *cognitive* (“knowledge of group membership”), *evaluative* (“value of group membership”) and *affective* (“emotional significance of group membership”) (Tajfel, 1978). Most existing work actually includes these dimensions, Jackson argues, but has organized it in diverse ways. Jackson then constructs a measure by drawing questions from existing work and allowing respondents to select their own group identity of choice. Using constrained factor analysis, he finds that the questions load onto the three theoretical dimensions as hypothesized.

Cameron (2004) and Leach et al. (2008) apply nearly identical methodologies in their research. Both start with a theoretical argument presenting what they believe to be the most important and potent dimensions of social identity attachment. They then use this theory to shape the questions they select (and edit) to measure attachment. Cameron (2004) argues that there are

three essential dimensions: *in-group ties*, *centrality*, and *in-group affect*. Using constrained factor analysis, the results indicate that three separate dimensions fit the data better than one or two forced factor loadings. Leach et al. (2008) argue for what they call a hierarchical model, with two general categories and five sub-dimensions within each category. The first category, “self-investment,” includes *solidarity*, *satisfaction* and *centrality*; the second, “self-definition,” includes *individual stereotyping* and *in-group homogeneity*. Similarly, Leach and authors compare multiple forced-factor loadings and find that the five by two structured model fits the data best. Both projects apply these methods on a variety of sample group attachment types including university, gender, nationality and continent-focused identities.

The most extensive theoretical work I have found to date, however, is the tremendously thorough literature review on (what they call) collective group attachment measurement conducted by Ashmore et al. (2004). The authors confirm that this phenomenon has been measured with many overlapping theoretical concepts. An important distinction they make is between the extent of an attachment and the outcome of an attachment, such as well-being or attitudes and behaviors. They then focus on the extent of attachment; in a way, they argue, that can be universally applied to collective identities.

Ashmore et al. (2004) note that there is no clear consensus on what dimensions matter most nor what has been most accurately measured. Some work gives the same exact construct completely different labels, even. (For a full review of all the theoretical constructs and their definitions, refer to Table 1 on page 83 of their work.) Their effort underscores the complexity of the existing literature and attempts to clear up some discrepancies by narrowing in on the elements that appear most relevant and replicated. From both a theoretical perspective and a measurement perspective, they focus on the following nine constructs (out of 17 total reviewed)



in theoretically conceptualizing collective identity: *self-categorization, evaluation, importance, attachment/interdependence, social embeddedness, behavioral involvement, self-attributed characteristics, ideology and narrative/knowledge* (Ashmore et al., 2004).

While Ashmore et al. (2004) list the questions associated with the categories, they do not engage in any empirical testing. Heere & James (2007) take on this task, adapting the questions from Ashmore et al. (2004)'s work to the measurement of sports team identity. After running an exploratory factor analysis, they find that "all constructs had only one factor with a eigenvalue larger than 1.00, indicating uni-dimensionality...all factor loadings were above 0.70 except for two items" (Heere & James, 2007, 78). This is one of the few unconstrained factor analyses in this body of work. They next use confirmatory factor analysis to evaluate Ashmore and author's constructs and report evidence of six categories instead of nine but note that there is quite a lot of messiness in overlapping factors and the correlations between factors. Heere et al. (2011) and Heere, James, et al. (2011) then edit this six-dimension measure to create even more specific questions related to the measurement of the collective identity of interest: local sport affiliations – city, state and university-specific.

This is just a small sample of the work that falls in the "universal" approach bucket. Other related work includes Smith et al. (1999)'s group attachment avoidance/anxiety measure, Schubert & Otten (2002)'s Overlap of Self, Ingroup and Outgroup measure, and Gómez et al. (2011)'s Identify Fusion/Identification. Even this relatively brief review makes clear that, however, at both the theoretical and methodological level there is a good deal of complexity and confusion in the existing literature.

## **“Group-Specific” Measures of Group Identity Attachment**

Phinney (1992)’s Multigroup Measure of Ethnic Identity (MEIM) is a good place to start in reviewing the “group-specific” approach to measuring social identity attachment, as it is a blend of the universal and specific approaches. Phinney set out to create a universal measure of ethnic identity, motivated by the fact that there were more than five different individual measures used to capture specific ethnic identities, e.g., Mexican American or Jewish American. Phinney both theorized universal components of ethnic identification that could be applied to any “ethnic group,” while also shaping the measure to *ethnic* group attachment specifically. Universal components of the MEIM include *self-identification*, *affirmation and belonging* and *attitudes towards other groups*, while other components of MEIM are rooted in the social and historical contexts of ethnicity in America. (In the literature reviewed above, there are authors that selected various questions from the universal aspects of Phinney’s work.)

Some argue further, however, that universality should not be the primary objective in measuring attachment to a group identity at all. For example, as highlighted by Sellers et al. (1998), “Although many ethnic groups have experienced discrimination and oppression in the United States, the form of oppression that African Americans have faced is unique” (18). The authors thus create the Multidimensional Model of Racial Identity (MMRI) that is specific to the experiences, history and group characteristics of being African American, and focus on “a micro view...important information about the depth” of this identity (34). Similar to MEIM, there are still some commonalities in the measure that are less African American-specific, such as *salience*, *centrality*, and *public and private regard*. The questions within these components are similar to and frequently appear in the measures reviewed above. Specific to the African

American experiences is the “racial ideology” category which includes *nationalism*, *oppression*, *assimilation* and *humanist* (Sellers et al., 1998, p. 24).

Martin et al. (1997) similarly root their Athletic Identity Measurement Scale (AIMS) in the unique experience of being an athlete. Athlete-specific questions in the measure include, for example, “I would be very depressed if I were injured and could not compete in sport” (77). The measure is also more broadly shaped by Social Identity Theory and related work, though, including questions like “Sport is the most important part of my life” and “Other people see me mainly as an athlete” (77), which are very similar in wording to questions included in more general social identity attachment measures.

Other examples of this kind of group-specific approach include Cross & Vandiver (2001) Cross Racial Identity Scale (CRIS), Huddy & Khatib's (2007) National identity and patriotism measure, Schwartz et al.'s (2012) American Identity Measure (AIM), Riggle et al.'s (2014) Lesbian, Gay and Bisexual Positive Identity Measure (LGB\_PIM) and Vinney et al.'s (2019) Fan Identity Scale. As with the work highlighted above, there is a blend of general underlying theory about psychological group attachment in combination with specific theoretical categories and question wording designed to capture the experiences distinct to these particular group experiences. Thus, the measures partially repeat the work done via the universal approach while also adding a multitude of questions to the field that can be useful in very specific research contexts.

The existing literature on partisanship as social identity, as well as the analysis that follows, adopts the “universal” approach. That said, my work will include many of the universally focused questions from the group-specific measures reviewed above (...not surprisingly, there's lots of overlap). As designed, the group-specific questions do not always

translate well to application of a different kind of group. There may be an opportunity for a more group-specific approach to the measurement of partisanship as social identity in the future. I consider this further in the concluding section.

### **Measurement of Political Partisanship as Social Identity**

As mentioned, there are thus far only a limited number of applications of social identity attachment measures to political partisanship. Those that exist mostly draw off previous measures designed with the universal approach, rooted in Mael & Tetrick (1992) or Brown & Williams (1984)'s work. Kelly (1988) was one of the first to apply social identity theory to the measurement of partisanship, converting the concepts outlined in Brown and William's qualitative interviews into efficient survey questions. Kelly focuses on not just in-group identification as it relates to self-concept and self-esteem, but also intergroup differentiation in political contexts. Kelly's paper doesn't attempt to define any particular component of social identity attachment specific to partisanship, per say. Instead, it uses the existing research to create ten survey questions, and then runs a principal component analysis finding that half of the questions load onto one dimension, while the other half load onto another. Kelly termed these dimensions as *positive affect* and *negative affect*. After examining the distribution (skewness) of the two factors, Kelly finds that the "best measure for discriminating between strong and weak party identifiers would be the extent of their agreement with positive items in the scale" (323). For the rest of the analysis in that paper, the five negative questions are dropped. And as with most existing work, the in-group identification proved to be a significant predictor of the outcome of interest – perceptions of group differentiation.

More recent work on measuring partisanship as social identity attachment is Greene (2004), adopted from Mael & Tetrick (1992). Greene makes the case that “Social identity theory yields important insights into the nature of partisan-related attitudes and partisanship itself... [and] can help us to better understand the role of partisanship in political attitudes and behavior as well as lead to more complete measures of partisanship” (137). To test this, Greene replicates the IDPG ten-item scale directly, only changing the group of focus to Democrat or Republican. The IDPG measure is compared to “partisan strength,” which is the seven-point measure of partisanship most commonly used in survey research (such as on the American National Election Studies) where respondents are asked whether they consider themselves a Democrat, Republican or what, followed by whether they consider themselves a strong or weak partisan. Greene first re-confirms the two components of *shared experiences* and *shared characteristics* via forced factor analysis and then finds that IDPG partisanship is only partially correlated with partisan strength ( $r=0.48$ ). Furthermore, Greene reports that IDPG partisanship strongly predicted ideology, partisan activity and party voting above beyond the traditional measure of partisan strength (which was only significant for ideology and voting).

Thus, initial evidence shows that partisanship measured as group attachment is distinct from measuring “partisan strength” and has different, potentially even more potent, power in predicting political outcomes. Building off this work, Huddy et al. (2015) conceptualize an SIT-focused measure of partisanship as *expressive partisanship* compared to *instrumental partisanship*. *Instrumental partisanship* is a “running tally of party performance, ideological beliefs, and proximity to the party in terms of one’s preferred policies” (1). While *expressive partisanship* is more of an emotional or psychological attachment to political parties as a group

identity. Huddy and coauthors aim to further test the idea that this distinction is critical in predicting different kinds of political outcomes.

Methodologically, Huddy and coauthors adopt the IDPG questions from Greene's (and Mael and Tetrick's) work, but only select four out of the ten items. There is little reasoning offered as to why they abbreviate the scale, nor why those four questions in particular were chosen instead of others. That said, they replicate Greene's method of pitting *expressive partisanship* against partisan strength (*instrumental partisanship*) on multiple samples. They find that partisanship as social identity is a better predictor of past and current/future political activity. They also find that respondents with stronger affective partisanship scores react more emotionally to political events (such as winning or losing an election). In summary, "We come down firmly on the side of expressive partisanship as a primary driver of campaign involvement, especially in close elections when the threat of electoral loss looms large" (Huddy et al., 2015, 15).

Bankert et al. (2017) then apply a version of the Huddy et al. (2015) measure to political party attachments in democratic, European multi-party countries (Netherlands, Sweden and the United Kingdom). The authors select five items from Mael and Tetrick (1992)'s IDPG and then add three new items for an eight-question partisan identity measure. There is, again, little explanation of why those five questions were selected over others, nor what decision-making process went into the inclusion or wording of the three additional questions (other than they were more specific to the European multi-party systems being investigated). Using Item Response Theory (IRT) the items in the measure proved to be relatively reliable, meaning that they nicely capture a wide variety of "information" relevant to the latent variable. In other words, the eight items are good at capturing the variation both at the high and low levels of party social identity.

In terms of whether this measure was consistent across the three different countries, the results were messier. Generally, though, it appears to measure similar enough concepts in all three. In terms of the predictive power of the identity scale compared to traditional measures, again Bankert et al. (2017) find it to be stronger in predicting political behaviors (such as likelihood of voting) and participation. The authors then re-run the IRT analysis and find that confining the measure to four items gets relatively the same results as the full eight-item scale, which is useful when thinking about the efficiency of applying these measures in survey work.

It is also worth noting that Devine (2015) adopts the IDPG 10-item measure to test Ideological Social Identity (ISI) as well. Thus, instead of political party identity, the authors tested psychological attachment to *conservative* or *liberal* identities. While they report that self-placed conservatives and liberals both scored higher on ISI, they only find significant results for conservatives and moderates in testing group-threat perceptions. Specifically, when these two groups are exposed to information about a hypothetical election, they score higher on ISI. This does indicate that election material is group-triggering, to some degree, but since ideology does not take shape as a physical group as much as the Republican and Democratic parties, I believe this project may be an under-representation of the effects of SIT application in U.S. politics.

In sum, the state of the “partisanship as social identity” field includes some variation of ten to four-item measures adopted from the universal approach to measuring psychological attachment to a group originally designed by Mael & Tetrick (1992). It appears the methodology mostly focused on replicating previous work. However, there is much ambiguity as to what went into the decisions to deviate from the original ten-item IDPG measure. Despite this ambiguity, the results further emphasize the value of a measure of this kind when it comes to predicting political behavior and attitudes.

Huddy and others have presented evidence that partisanship as *social identity* is an important moderator of outcomes in political science research, and thus worthy of deeper consideration. In fact, Huddy et al. (2020) reviewed partisanship measures in the political science field across the world and find that measures with more variation in the degree of strength and direction are useful in predicting outcomes, arguing: “that there is considerable value in measuring partisan identity with a multi-item scale” (119). This is in line with decades of previous work on SIT in psychology.

In the field of communication, partisanship as traditionally measured has proven to be a strong predictor of media effects as well. This is especially evident in work on selective exposure (e.g., Stroud, 2008), hostile media effect (e.g., Gunther et al., 2001; Perloff, 2015), information credibility perceptions (e.g., Metzger et al., 2020) and general motivated reasoning (e.g., Bolsen et al., 2014), and misinformation belief (e.g., Thorson, 2016), to name a few. But little work in communication has expanded to examine the impact of *the social identity attachment* operationalization of partisanship. I hypothesize that measuring group attachment to political parties in this way matters and could lead to, at best, stronger predictions of political media effects, or, at least, reveal interesting heterogeneity in media effects outcomes. This will be the focus of Chapter 4. As outlined above, the objective of this chapter is to develop an efficient measure of partisan social identity attachment, which is an essential first step towards testing this broader hypothesis.

## **A Data-Driven Approach**

The preceding review of the group attachment literature suggests the following. First, there is no single, agreed-upon theory of multiple dimensions of social identity attachment, and



there is no agreed-upon method of measuring it. Well-reasoned and well-researched work on the very same topic has led to quite different areas of theoretical focus and completely different labeling or categorizing of ideas. This highlights the potentially arbitrary nature of past measurement decisions. Readers are often left wondering *why* one author chose to focus on “centrality” while another focused on “salience” – two theoretically overlapping ideas yet worded quite differently in survey questions. With about 17 different theoretical constructs of collective identity reviewed by Ashmore et al. (2004) and at least two, or even three or four, different survey questions designed to measure those elements across other work, it’s no surprise the field has yet to land on a universally accepted and efficient measure. My intention is not to advocate that measures be constructed absent of theory; but rather that going forward it’s most useful to explore the empirical evidence of subdomains rather than assume them.

Second, I believe there are potential methodological issues with validity of measures where the wording of the questions is designed to fit the theoretical priors, and the authors subsequently report confirmatory factor analysis results supporting the pre-designed model. Take Cameron (2004) and Leach et al. (2008) who both make compelling arguments for adopting their particular perspective on how the dimensions of social group attachment should be organized and operationalized in measurement. In each case, once the authors laid the theoretical groundwork, they selected questions (and created their own questions) that they believed most directly captured those constructs. Leach et al. (2008) explains this process: “Through group discussion, the authors reached a consensus about what items adequately indicated each component. Items deemed overly general, vague or indicating multiple components were excluded from consideration” (150). And Cameron (2004), for example, uses the entire 10-item measure from Brown et al. (1986), but then selects only specific subscales from Luthanen &

Crocker (1992), Bollen and Hoyle (1990) and Aron et al. (1992) that best adapt to his model, rather than testing those entire measures (247). They then use confirmatory factor analysis and report that the model of best fit matches the number of dimensions outlined in the theoretical argument, which is not surprising. This method of crafting measurement around theory is not only logical, but also expected within the standard practices of survey research. It also proves that the questions hand-selected are, in fact, measuring concepts distinct from each other in the exact pattern they are desired to (internal validity, if you will). My concern is that by using this method, the authors are not able to properly externally validate their measures (and the theory underlying the measures) against *the other existing measures* of social identity attachment. Readers are still left having to simply buy-in to one particular scholar's theoretical argument over another. The analysis presented in this chapter is my attempt to address this limitation.

Although these observations may seem critical in nature, I want to make clear, again, that the methods used in previous work are well within the expectations of social science research. Without theory, the idea of social identity attachment itself wouldn't exist. Measurement *must* be grounded in a basic understanding of what the object being studied is. The messiness in measurement, I believe, has developed from the challenge of trying to articulate a deeply complex phenomenon that has both universal properties and characteristics, while also potentially shifts depending on the context. On the one hand, Brown & Williams' (1984) call for an easy to apply measure of group attachment was rooted in their (and subsequently many, many others) observation of the importance and centrality of group attachment in understanding human behavior. On the other hand, scholars such as Sellers et al. (1998) and Martin et al. (1997) suggest that adopting a "one-size-fits-all" approach severely limits our ability to measure the depth of impact social identity attachment has on specific groups of people. Martin et al. explain,

for example, "...athletes with an exclusive athletic identity may have emotional difficulty adjusting to non-sport participation" which has been proven to be directly related to the mental health of those athletes (75).

This line of argument has merit. As do the repeated efforts by scholars to articulate and demonstrate the multidimensional nature of psychological attachment to a group. For the purposes of investigating the impact of partisan social identity attachment on media effects outcomes, however, I believe the first step is to develop an efficient and potent measure that can be easily deployed in survey work and be tested against the status quo measure: partisan strength. From there, the groundwork will be laid for others to explore political party group-specific dimensions and better theorize the underpinnings of this particular kind of attachment.

The analysis conducted in this chapter attempts to address the potential pre-selection bias found in past work by including as many theoretical constructs as possible that seem relevant and present in the literature (though there are cases where there is overlap). By selecting a wide variety of questions from various sources to measure those concepts, all dimensions are allowed to compete with one another. My choices are not motivated by any one particular theory then; rather, they are strictly empirical – aiming for full coverage of dimensions and breadth in questions – with the intention of letting the data indicate its own "best fit."

## **Methodology**

A two-wave survey was designed with the objective of exploring the measurement of political partisanship in the U.S. as a psychological group attachment and of testing its impact on political communication effects. The survey was conducted using the online panel respondent database maintained by the data and insights service, Dynata. The respondents were paid a small

fee to participate in the survey, contacted digitally and completed the survey online. From this online panel, Dynata restricted the sample to self-identified political partisans in the U.S., then focused on approximately nationally representative sampling in terms of basic demographics (age, gender, race, etc.) within those targets.

Because the primary focus of this project is to compare partisanship as social identity (which I'll refer to as PSIM) to traditional measures of partisan strength (which I'll refer to as PID), the survey specifically targets those who identify as a member of one of the two major political parties in the U.S.: Democrats and Republicans. This decision was made given the focus of the next chapter of this project, which builds on the current chapter to explore how strength of identification (i.e., the *degree of social group identification*) with a political group predicts media effects compared to PID. I recognize that by pre-selecting respondents who identify with the groups of interest the results reported in this chapter may not be easily generalized to a sample including non-identifiers. Re-testing PSIM on a broader sample (which would simply include more independents or non-identifiers) could reveal additional insights into the measure. However, given the large variation in partisan social identity found in the current sample I anticipate that results presented here (and in the next chapter) would not fundamentally change. This is discussed further in the conclusion.

The first wave of the survey was distributed online from August 31, 2020 – September 15, 2020, the final push in the 2020 U.S. presidential election, to just over 2,300 respondents (dropping incompletes). The second wave was distributed to the same respondents from October 26, 2020 – November 6, 2020, leading up to Election Day, with about a 47% response rate. The analysis presented in this chapter focuses almost exclusively on data collected from the first wave as it is where the PSIM questions are administered. Below I will explore the results of the

PSIM measurement and how it relates to PID and other measures. The second wave includes a media exposure experiment, and thus is more focused on testing the impact of PSIM versus PID on media effects outcomes – which will be the focus of Chapter 4.

### *Wave 1: Survey Sample*

As mentioned above, this survey specifically targeted people who identify, at least to some loose degree, as Democrat or Republican. By doing so, the number of cases is sufficient to explore variation in attachment *within* those identity categories. The sample includes 1143 Democrats, 1082 Republicans and 133 independents.

Because of this targeting, the sample is understandably more politically interested than what one would expect from a nationally representative sample. 79% of the sample reported being somewhat, very or extremely interested in politics. In terms of demographics, gender was about evenly split with 51% reporting as identifying as female, 48% male, and about 1% non-binary or other. This holds relatively true within political party as well, especially for Republicans with 50.8% male and 49.2% female. Democrats lean slightly female with 54.3% compared to 45.7% male. Age was evenly distributed, starting with the voting age of 18 through 85 or older. The sample skews slightly educated, with 60% of respondents reporting some sort of college experience and 40% reporting high-school diploma or less. A little less than 50% of the sample is employed full time, while most others report being retired, student or part-time employed. Finally, the distribution on racial identity for the sample maps relatively well onto national averages. The sample is about 14% Black, 70% white, 7% Hispanic, Latinx or Spanish origin (which is a bit low), 5% Asian and about 3% American Indian, Alaskan Native or Other.

### *Partisanship as Social Identity Attachment Measurement: PSIM*

The critical task at hand is exploring the measurement of partisan social identity with respect to the extensive existing literature on the subject. I started by documenting all the questions included in 12 of the social identity attachment measures from the work reviewed above, removing repeated questions. The resulting list included 112 questions covering 17 different theoretical constructs or dimensions. From there, I narrowed the theoretical concepts down to 14 (ending up with 13, see Table 3-1) based on obvious instances of overlap and guided by the work of Ashmore et al. (2004). I then narrowed the questions down to 37 based on the following criteria.

First, I selected questions that appeared in at least three or more distinct measures. By distinct I mean non-replicated. For example, Greene (2004) was a direct replication of Mael and Tetrick (1992), so a question from that measure would only count as one, rather than as appearing in two measures. But if a question from Greene (2004)/Mael and Tetrick (1992) also appeared in Sellers et al. (1998) and Jackson (2002) where no complete replication was done, I counted it as appearing in *three* distinct measures. Second, all 13 theoretical constructs were assigned at least two survey questions. To select the questions to cover all these constructs, I returned to the authors who had originally developed the constructs and selected from their measure(s) directly. Full tables reporting the original pool of survey questions and corresponding authors are included in Appendix B, Tables B1 and B2.

As described above, my goal was to pull from as wide a variety of theoretical dimensions as possible and sample a broad variety of survey questions. The resulting social identity attachment questions are listed in Table 3-1, including the theoretical constructs they operationalize and the list of authors from where they appeared in the literature. Note that the

first theoretical construct, *self-categorization*, is described in the literature as being the conscious opting into the group and is measured using basic questions like “Do you identify as a member of X?” Because the respondents in the survey are already being asked this question in the traditional measure of partisan strength (PID), it was not additionally included in the partisan social identity measure (and is not included in the 37-question count, reducing the theoretical constructs to 13).

*Table 3-1: Starting Social Identity Attachment Measure Questions*

<b>Question</b>	<b>Theoretical Construct</b>	<b>Author(s)</b>
<i>I am a () ?</i>	<i>Self-categorization – captured by PID</i>	<i>Jackson (2002)</i>
<i>Do you identify as a member of ()? / I identify with ().</i>	<i>Self-categorization – captured by PID</i>	<i>Brown &amp; Williams (1984)/Kelly (1988) Ashmore et al. (2004)/Heere &amp; James (2007)</i>
In general, I am glad to be a ().	Affect / Attachment	Brown & Williams (1984)/Kelly (1988) Kashima et al. (2000) Jackson (2002) Ashmore et al. (2004)/Heere & James (2007) Cameron (2004) Leach et al. (2008)
I feel good about being a member of ().	Affect / Attachment	Sellers et al. (1998) Jackson (2002) Ashmore et al. (2004)/Heere & James (2007) Cameron (2004) Leach et al. (2008)
I'm proud to be a ().	Affect / Attachment	Sellers et al. (1998) Kashima et al. (2000) Jackson (2002) Ashmore et al. (2004)/Heere & James (2007)
I often regret that I am a ().	Affect / Attachment	Sellers et al. (1998) Jackson (2002) Cameron (2004)
Being a () is an important part of my self-image.	Importance / Self-concept / Centrality	Sellers et al. (1998) Kashima et al. (2000) Jackson (2002) Ashmore et al. (2004)/Heere & James (2007) Cameron (2004) Leach et al. (2008)
Being a () is important to my sense of what kind of person I am.	Importance / Self-concept / Centrality	Sellers et al. (1998) Kashima et al. (2000) Jackson (2002)

		Ashmore et al. (2004)/Heere & James (2007) Cameron (2004) Leach et al. (2008)
Being a () is important to me.	Importance / Self-concept / Centrality	Ashmore et al. (2004)
When someone criticizes () it feels like a personal insult.	Interdependence / Common Fate	Greene (2004) Ashmore et al. (2004)/Heere & James (2007) Huddy et al. (2015)
()'s successes are my successes.	Interdependence / Common Fate	Jackson (2002) Greene (2004)
When I talk about (), I usually say "we" rather than "they"	Interdependence / Common Fate	Jackson (2002) Greene (2004) Ashmore et al. (2004) Huddy et al. (2015)
If a story in the media criticized (), I would feel embarrassed.	Interdependence / Common Fate	Mael and Tetrick (1991) Jackson (2002) Greene (2004)
I would be depressed if () failed.	Interdependence / Common Fate	Martin et al. (1997) Jackson (2002)
I have a number of qualities typical of ().	Fit / Typicality	Mael and Tetrick (1991) Kashima et al. (2000) Jackson (2002) Greene (2004) Ashmore et al. (2004)
I have a lot in common with other ().	Fit / Typicality	Jackson (2002) Cameron (2004) Leach et al. (2008) Huddy et al. (2015)
My background is similar to that of most ().	Fit / Typicality	Kashima et al. (2000)
I act like a () person to a great extent.	Behavior	Jackson (2002) Greene (2004) Ashmore et al. (2004) Huddy et al. (2015)
I participate in activities supporting ().	Behavior	Ashmore et al. (2004)/Heere & James (2007)
I feel strong ties with other people who support the () party.	Solidarity / Connectedness	Brown & Williams (1984)/Kelly (1988) Kashima et al. (2000) Cameron (2004)
In a group of (), I really feel that I belong.	Solidarity / Connectedness	Sellers et al. (1998) Cameron (2004)
I feel committed to ().	Solidarity / Connectedness	Leach et al. (2008)
I often think about the fact that I am ().	Cognitive	Martin et al. (1997) Cameron (2004) Leach et al. (2008)
I am not usually conscious of the fact that I am ().	Cognitive	Cameron (2004)
I'm very interested in what others think about ()	Evaluation / Attitude	Jackson (2002) Greene (2004)



		Huddy et al. (2015)
Overall, () are viewed positively by others.	Evaluation / Attitude	Sellers et al. (1998) Ashmore et al. (2004)/Heere & James (2007)
In general, others respect ().	Evaluation / Attitude	Sellers et al. (1998) Ashmore et al. (2004)/Heere & James (2007)
I feel that () have made major accomplishments and advancements.	Evaluation / Attitude	Sellers et al. (1998)
I am aware of the tradition and history of ().	Knowledge / Narrative	Ashmore et al. (2004)/Heere & James (2007)
I know the ins and outs of the () platform.	Knowledge / Narrative	Ashmore et al. (2004)/Heere & James (2007)
I have knowledge of the successes and failures of ().	Knowledge / Narrative	Ashmore et al. (2004)/Heere & James (2007)
() have a lot in common with each other.	Homogeneity	Leach et al. (2008)
() act very similar to each other.	Homogeneity	Leach et al. (2008)
It is important to me that others identify me as ().	External Perception In-group	Jackson (2002)
Other people mainly see me as a ().	External Perception In-group	Martin et al. (1997) Kashima et al. (2000)
I prefer to see (ingroup) as distinct from (outgroup).	Distinction from Out-group	Jackson (2002)
(outgroup) people are different from (ingroup) people.	Distinction from Out-group	Jackson (2002)
Most of my friends are ().	Social Embeddedness	Martin et al. (1997) Ashmore et al. (2004)
Being () is not a major factor in my social relationships.	Social Embeddedness	Sellers et al. (1998)

Respondents were presented with the 37 questions separated into six “blocks,” with each block including a randomized pairing of theoretical concepts. For example, one block includes the questions from the *affect/attachment* and *behavior* dimensions. The questions that operationalize each theoretical concept are also kept together – which appeared to be a common practice of the group attachment measures reviewed in this chapter. Hence, all the *affect* questions are presented first, followed by all the *behavior* questions in that block. Each block had about six or seven questions total as to not overwhelm the respondents. The order of the six

blocks were also randomized for every respondent. Respondents were instructed at the beginning of each block to do the following: “When thinking about your political party, please rate how much you agree with the following statements.” They are then asked to rate the statements on a five-point scale from strongly agree to strongly disagree, with neither agree nor disagree as the middle category. The five point agree/disagree scale was selected, again, because of its commonness in the methodology of the existing group attachment measures. This approach introduces many layers and opportunities for variation in responses. Respondents can vary significantly in PSIM strength within an individual question, within individual theoretical dimensions, or within the entire measure overall.

#### *Traditional Measure of Partisanship: PID*

The measurement of partisanship most frequently used across political science and political communication research asks respondent to select the strength of their identification with a political party group categorically. This question can also be found in long-standing national survey projects such as the American National Election Studies (ANES), as was used in the analysis in Chapter 2. The question is structured as follows: (1) respondents are asked, “Generally speaking, do you usually think of yourself as a Republican, a Democrat, an Independent, or what?”; (2) based on their choice the respondents are then asked, “Would you call yourself a strong Republican/Democrat or a not very strong Republican/Democrat?”; and (3) if respondents selected Independent, they are asked, “Do you think of yourself as closer to the Republican or Democratic party?” In this survey, PID is then converted to a seven-point scale with 0 in the middle representing those who are Independents or do not identify with a party. The numbers (-1) through (-3) represent Democrat leaners, weak Democrats and strong Democrats,

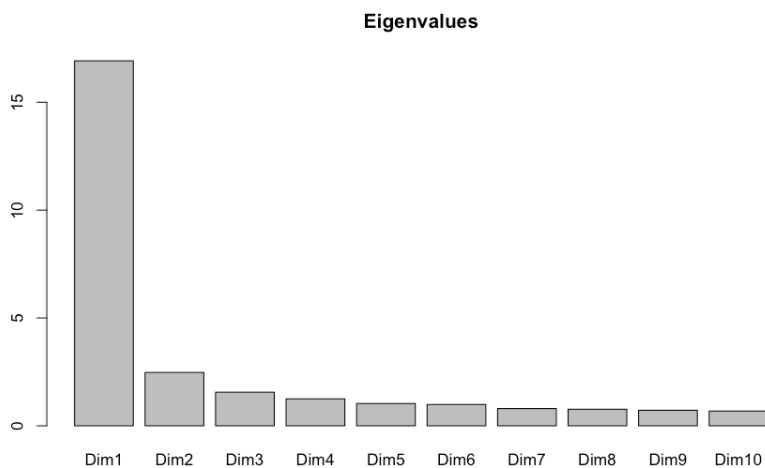
respectively, and the numbers 1 through 3 represent Republican leaners, weak Republicans and strong Republicans, respectively.

## Results

### *The Dimensions of Partisanship as Social Identity Attachment*

I started by running an unconstrained principal components analysis of the 37 PSIM questions. As described in detail above, my objective is to *not* introduce any theoretical priors into my analysis, thus I will initially not constrain the analysis. This allows the data to dictate the dimensions. The results produce a possible 37-dimension model (as many dimensions as there are questions). However, based on the eigenvalues represented in Figure 3-1, an overwhelming proportion of the variance is captured by the first dimension.

*Figure 3-1: Eigenvalues for the unconstrained PCA of PSIM (top 10 dimensions only)*

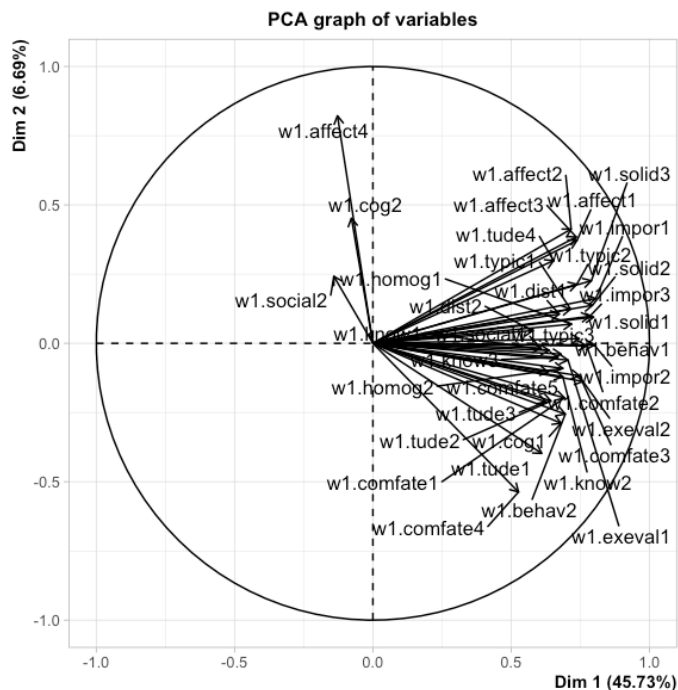


This result is in line with the findings of a similar analysis conducted by Heere & James (2007). They included all the questions from Ashmore et al. (2004)'s theoretical constructs in an

unconstrained factor analysis and find that the questions naturally fall on one dimension. My analysis similarly shows that about 92% of the questions load onto dimension one with loadings above 0.57. The only questions that do not fall on this dimension are the questions that are negative or reverse in language. For example, “I am *not* usually conscious of the fact that I am Republican” (emphasis added) is a question in which the respondent must respond to a negation rather than affirmation of the group identity attachment. The difference between dimensions appears to not be substantive, but rather due to question form.

Figure 3-2 illustrates variable loadings on each of the first two dimensions. *Social2*, *cog2* and *affect4* are the only three negative questions in 37-item battery; each fall on dimension two, which accounts for just 6.7% of the variance. Dimension one, in contrast, accounts for about 45.6% of the variance in the 37 variables. Although not shown here, note that the results are the same when the analysis is restricted to just Democrat or just Republican respondents.

Figure 3-2: Unconstrained PCA analysis of PSIM, Dimensions 1 and 2



The factor loadings themselves are reported in Table 3-2, for the first two dimensions.

The top ten questions that load onto dimension one are bolded. Again, in line with previous work done by Bankert et al. (2017), I find that an index based on these top ten questions (PSIM10) is highly correlated with an index based on all 37, at  $r = 0.949$ . Further, the top four questions that load onto dimension one are italicized in Table 3-2; and the index based on these four questions is also highly correlated with the full 37-item index, at  $r = 0.912$ . These results suggest that using the top ten questions – or if a project is even more constrained by time and money, using the top four – produces a measure of PSIM that is very similar to what is obtained with a much longer 37-item battery. It's important to note that the high correlation between the top 10 and top four questions with the whole battery may be, in part, due to respondent fatigue and response set bias. In facing so many similarly structured questions the respondents may have been very consistent in their answers as a matter of ease in getting through a rather long survey. Further, this is a non-representative sample where I expect high levels of political interest across the board. This may also have inflated the high correlation, and is a limitation addressed in the discussion section.

*Table 3-2: Unconstrained PCA Factor Loadings of PSIM, Dimensions 1 and 2*

Theoretical Construct	Dimension 1	Dimension 2
<b>affect / attachment 1</b>	<b>0.738</b>	0.372
affect / attachment 2	0.717	0.413
affect / attachment 3	0.735	0.384
affect / attachment 4	-0.128	<b>0.822</b>
<b>behavior 1</b>	<b>0.746</b>	0.017
behavior 2	0.696	-0.256
<i>importance / centrality 1</i>	<i><b>0.806</b></i>	<i>0.162</i>
<i>importance / centrality 2</i>	<i><b>0.8</b></i>	<i>-0.006</i>
<i>importance / centrality 3</i>	<i><b>0.784</b></i>	<i>0.097</i>
<i>solidarity / connectedness 1</i>	<i><b>0.798</b></i>	<i>0.095</i>
<i>solidarity / connectedness 2</i>	<i><b>0.794</b></i>	<i>0.137</i>
<i>solidarity / connectedness 3</i>	<i><b>0.79</b></i>	<i>0.226</i>
typicality / fit 1	0.715	0.124
typicality / fit 2	0.737	0.213
typicality / fit 3	0.68	-0.039
knowledge / narrative 1	0.638	-0.026
knowledge / narrative 2	0.687	-0.121
knowledge / narrative 3	0.669	-0.051
common fate 1	0.693	-0.197
<b>common fate 2</b>	<b>0.773</b>	-0.009

<b>common fate 3</b>	<b>0.747</b>	-0.117
common fate 4	0.526	-0.537
common fate 5	0.634	-0.104
homogeneity 1	0.718	0.069
homogeneity 2	0.687	-0.091
cognitive 1	0.68	-0.289
cognitive 2	-0.078	<b>0.452</b>
attitude / evaluation 1	0.611	-0.398
attitude / evaluation 2	0.644	-0.208
attitude / evaluation 3	0.624	-0.211
attitude / evaluation 4	0.653	0.299
external perception, in-group 1	0.705	-0.061
external perception, in-group 2	0.76	-0.138
distinction from outgroup 1	0.674	0.106
distinction from outgroup 2	0.578	0.046
social embeddedness 1	0.607	-0.017
social embeddedness 2	-0.141	0.242

An important part of this analysis was the decision to not restrict questions based on a set of theoretical priors. It is interesting to note, however, that the questions which most strongly load onto the first dimension are from a very limited number of theoretical constructs. The top six questions are exclusively representative of two theoretical dimensions: *importance/centrality* and *solidarity/connectedness*. In contrast, none of the *attitude/evaluation* questions make the top 25. This could indicate that something about those questions in particular or the theoretical constructs they represent is especially potent at capturing this phenomenon, which may be a starting point for interesting future work.

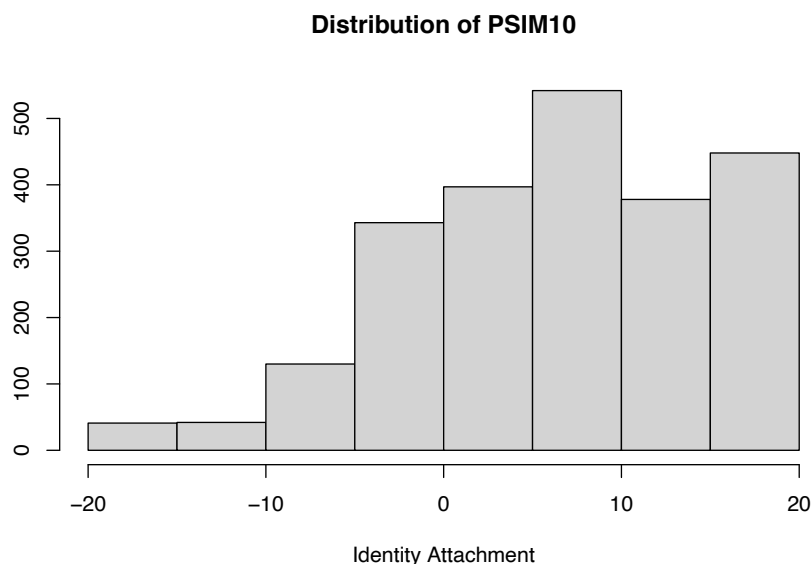
Do the same results remain when using a more constrained approach to factor analysis? In short, yes. Appendix B Tables B3 – B5 show the results testing various numbers of factors, restricted to three factors, and varimax rotated and not. The results hint at some small differences across questions, but mainly support this one-factor solution.

### *Comparing PSIM and PID*

The next analysis focuses on exploring the relationship between PSIM, PID and previous measures of group attachment. Distributions of PSIM10 and PID are represented in Figures 3-3

and 3-4, respectively. For PSIM10, the 10 questions are measured using a five-point scale (strongly agree/agree/neither/disagree/strongly disagree) which was converted to a numeric scale

*Figure 3-3: Distribution of Partisan Social Identity Measure, Top 10 Questions*



(2 representing strongly agree and -2 representing strongly disagree). The responses for the 10 questions were then added resulting in -20 representing no psychological attachment to the group while 20 indicates extremely strong attachment to the group. Given the survey sample targeted self-identifying Republicans and Democrats, most of the distribution of PSIM10 is above zero as expected. And the distributions looking at Democrats and Republicans separately are both very similar to Figure 3-3. There is quite a bit of variation above 0, however, and some below 0 as well indicating there is potentially meaningful variation in PSIM10, which will be discussed in more detail below. Figure 3-4 shows the distribution for PID and highlights the degree to which partisans were targeted in this sample. The majority of respondents report being strong Democrats (represented by -3) and strong Republicans (represented by +3).

Figure 3-4: Distribution of Partisan Strength Measure

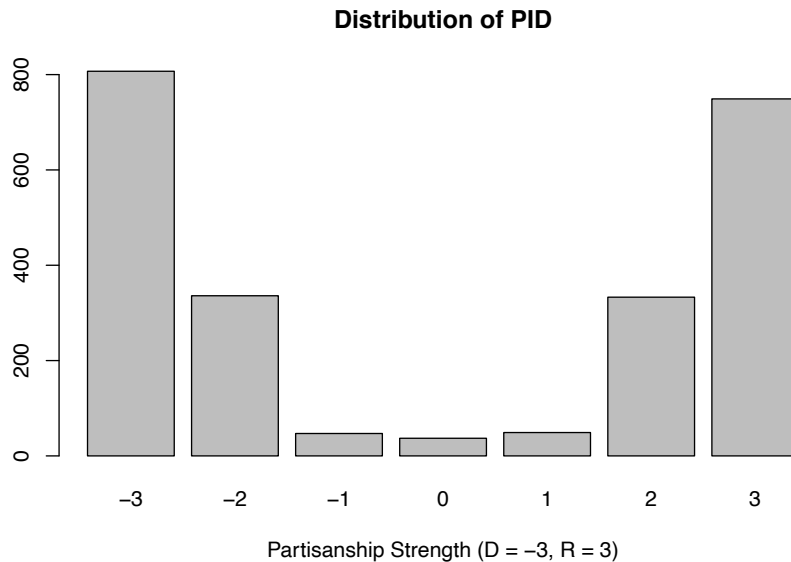


Table 3-3 shows the correlation coefficients of PSIM to PID and other measures. PID is collapsed into a four-category numeric scale (0 – 3) for this analysis where 0 represents not identifying with Democrats nor Republicans, and 3 represents both Democrat and Republican respondents who consider themselves “strong” identifiers. Thus, PID here is simply a measure of strength that does not distinguish between the two parties allowing for more direct comparison with PSIM. I also draw from a random sample of measures from the literature reviewed above. Note, of course, the correlations to previous measures are limited by the fact that not *all* the questions from previous measures are included. For example, there are only seven out of the ten questions from Greene (2004) included in the survey. And from here on, I also almost exclusively use the top 10 loaded questions, referred to as PSIM10 in this table, but then calling it simply PSIM in all further analyses. PSIM ALL (all 37 questions) is included only in the comparison to PID.



*Table 3-3: PSIM correlations to PID and other SIT measures*

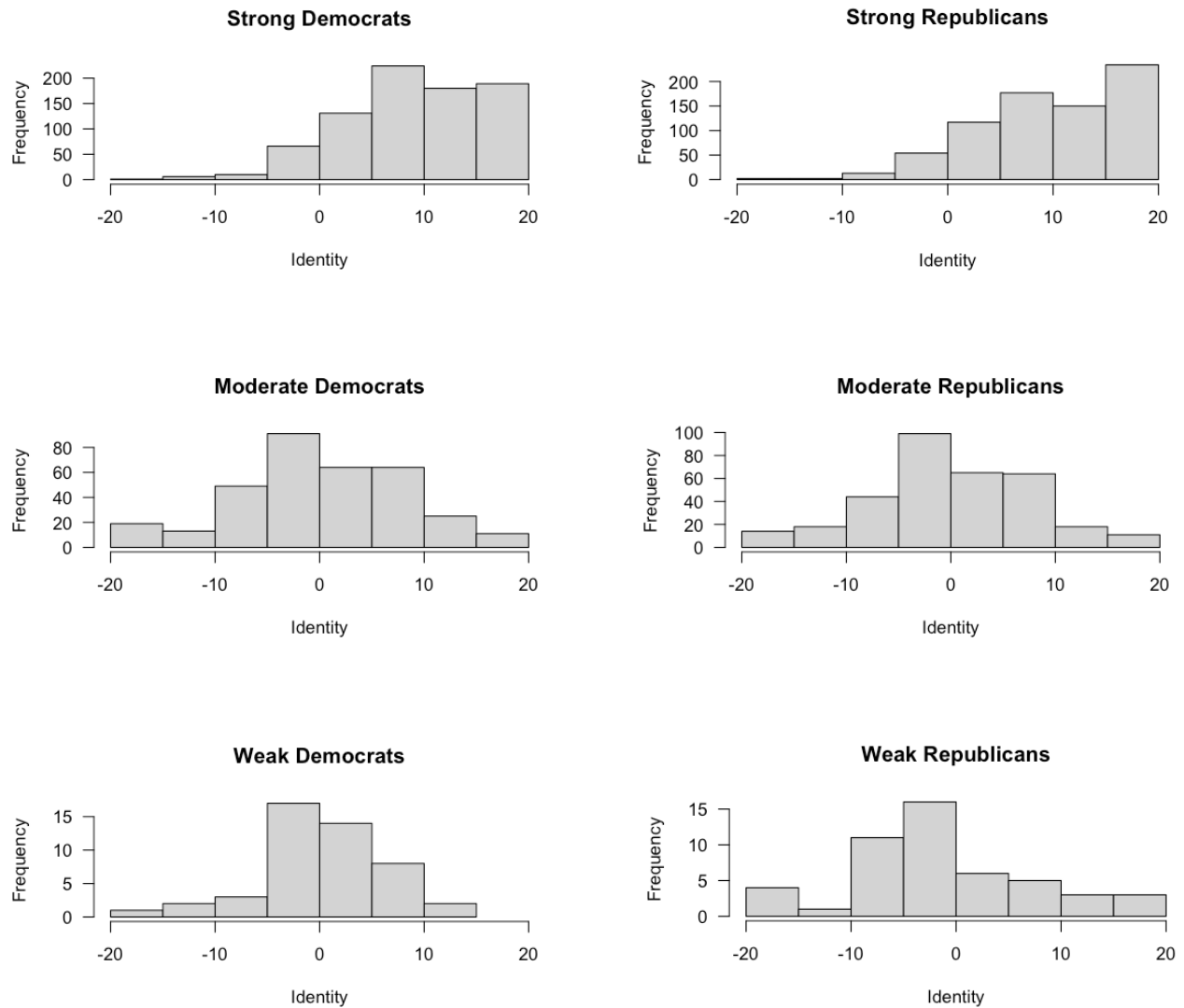
<b>Measure Comparison</b>	<b>Coefficient</b>
PSIM10 / PID	0.490
PSIM ALL / PID	0.463
PSIM 10 / Mael & Tetrick, Greene IDPG	0.840
PSIM 10 / Bankert et al.	0.877
PSIM 10 / Kashima et al.	0.969
PSIM 10 / Sellers et al.	0.905
PSIM 10 / Ashmore et al., Heere & James	0.915

First note that the correlations between PSIM and measures from previous literature are highly correlated. This is not surprising since the questions in PSIM are directly pulled from these measures. It also indicates that the top 10 questions from dimension one are likely questions that commonly appear across the previous work.

In line with the findings of Greene (2004), I find that the PSIM measure is only moderately correlated with PID. Only about a quarter of the variance of one is explained by the other. This indicates that while the measures may be related, they are likely measuring two distinct concepts. I explore this in more detail in Figure 3-5. Remember, along the PSIM x-axis, a “20” results from extremely strong agreement with the statements of identity attachment with the party group, while “-20” results from strong disagreement with the statements, or little to no identification with the party group. Within the PID categories there appears to be quite a lot of variation in PSIM. For moderates, PSIM appears to be mostly evenly distributed and for weak identifiers, the majority clusters around 0 in PSIM. The variation in the strong PID categories, however, is rather striking. Many people who opted into the “strong” partisan category score only moderately (between 0 and 10, for example) on PSIM.

It is possible, of course, that the variation within PID categories is simply noise resulting from a complex, multi-item battery. On the other hand, this could also indicate that PSIM and PID are connected, but distinct measures, and that the variation in PSIM captures important information missed by PID. These possibilities can be explored, and potentially resolved, by further testing of PSIM and PID in predicting meaningful outcomes. This is the focus of the next chapter of this project.

*Figure 3-5: Variation in PSIM within PID categories*



## Discussion

Much scholarship has been devoted to the theorizing and measurement of psychological attachment to a group over the past four or five decades. There is widespread agreement that this phenomenon is complex, multidimensional, and essential to understanding how humans think and behave. Humans are, after all, a social group-focused species. This complexity, though, has also led to a wide variety of theoretical and methodological approaches to measuring it. The central objective of this chapter has been to highlight the often conflicting and ambiguous decision making that has made it challenging for the fields of psychology and political science to land on one, universal and easy to apply measure.

The data I present here is not necessarily an attempt to completely resolve this challenge as much as being a demonstration of an alternative, more efficient approach. My goal was to respect the wealth of existing work by *not* re-theorizing the social group attachment for partisanship, but instead eliminating theoretical priors or biases on the analysis. I furthered this effort by pulling from as wide a variety of theories and questions as possible to test a partisan social identity measure. This method is also completely transparent with the reader in outlining the decision-making process behind which questions are selected. Namely, the selection is based on the results of the analysis rather than the other way around.

The initial results presented in this chapter are promising where the concise measure of partisan social identity is concerned. First, although 37 questions were included in the survey, it appears that only ten (or even four) are sufficient for capturing psychological attachment to a political group. Along those lines, the questions overwhelming load onto one dimension leading to less measurement complexity as well. In other words, a win for efficiency. Second, PSIM is only partially correlated with the traditional measure of partisan strength. And as demonstrated in

Figure 3-5, there is quite a wide variety of social identity attachment strength *within* the PID measure. This evidence confirms work done by Greene (2004), Huddy et al. (2015) and Bankert et al. (2017) that social identity attachment is, in fact, a *distinct* concept from what is measured by traditional partisan strength.

It has been clearly stated throughout this chapter that the objective was to remove bias from the measure and focus on application in surveys. Therefore, the one-dimension, data-driven measure presented here unfortunately ignores an essential agreed-upon characteristic of SIT: that it is multidimension in nature. Looking at the top ten questions that loaded onto the first dimension in the analysis qualitatively, there is clearly something about the *importance/centrality* and *solidarity/connectedness* theoretical constructs that drives the measure. This is an interesting starting point for future work. The approach presented here also sets aside the important arguments made by Sellers et al. (1998) and others who have approached the measurement of group attachment starting from the unique experience of a group. I have not, nor will I in the confines of this project, consider the particular thoughts, experiences and behaviors that may define *political party* group attachment in the U.S. distinctly from other types of group attachments. But there's plenty of anecdotal evidence that this kind of project is worth pursuing. For example, it is rare to find an entire socio-political system, backed by billions of dollars of marketing efforts, that pits *groups against each other on a regular basis* as is done between the political parties in U.S. elections. The nature of an election-based political system that, for better or worse, forces people into one group or another is an especially exceptional experience that could (maybe, should) be considered in understanding the psychological attachment citizens have to these groups.

Furthermore, the choice to limit the survey sample to respondents who pre-identify with a political group may bias the results reported in this chapter. As explained above, this choice was made in an effort to lay the groundwork for the next chapter, which will focus on how differences in the degree to which one *identifies* with a political party may impact media effects outcomes *distinctly* from traditional measures of partisanship. That being said, it may well be critical to re-run the analyses presented here on a broader sample which includes more variety of political identification – particularly non-identifiers or independents.

Finally, and importantly going into the next two chapters, the ten-item measure of PSIM is going to have much less noise than a single-item measure such as PID. This will need to be considered when comparing the two measures against each other in predicting outcomes. Ten items are also a lot more costly in terms of time and resources than deploying a single-item question. It is the objective of the next analyses to consider the potential benefit – or in which research contexts there is benefit – of using the more complex measure.

Given these limitations, though, my goal is to build the foundation from which political communication scholars specifically can explore such complexities in the future. The objective of the next chapter is to further establish that partisanship operationalized as a group attachment is distinct from the previous status quo of partisan strength. Using PSIM, Chapter 4 will also test the hypothesis that this difference matters in predicting and moderating political communication effects.

## Chapter 4 A Social Identity Approach to Partisan Media Effects

Scholars of political communication have established that media have the power to influence voter emotions, attitudes about policies or candidates and behaviors, such as participation in political campaigns and elections. That said, the literature also makes clear that media do not affect every voter in the same way. In fact, voters can be influenced by media messages in strikingly diverse ways. One of the central and most compelling bodies of work in this field uses *political partisanship* as means of predicting (and moderating) these heterogeneous media effects.

A common theme throughout the partisanship-focused political media effects literature is the use of Social Identity Theory (SIT) as a framework to understand the deeper, psychological mechanisms that may be driving the impact of partisanship. This is particularly true for effects hypothesized to be activated through cognitive dissonance, such as hostile media perceptions and motivated reasoning. Despite the fact that growing work in political science continues to build a case for partisanship operating as a *social group identity attachment* (and thus calling for improved measurement, i.e., Greene, 2004; Huddy et al., 2015; Bankert et al., 2017), however, there is very political communication scholarship that applies this notion to our understanding of media effects directly. Even for work that argues *strength of partisanship* matters for media effects, the degree of strength is most often three self-reported categorizations: strong, moderate/weak or leaner. I argue that if SIT is the foundation of the theory driving the study of these effects, it should be properly actualized in measurement of the effects as well. This gap in the methodology of political communication scholarship is what I explore here.

As reviewed in the previous chapter, there is a large body of work in psychology that suggests there are aspects of attachment to a political group that may not be well captured by traditional measures. I have synthesized the complexities of that literature and arrived at a measure that incorporates multiple theoretical dimensions yet is simple enough to be deployed in time- and space-limited survey research. The partisan social identity measure (PSIM) developed in Chapter 3 is a 10-item battery of questions that aims to capture variation in psychological attachment to a group, operationalizing concepts such as centrality of the group identity, solidarity with other members of the group, affect and perceptions of tied fate with the group, for example. The traditional measure of partisan identity (PID) – used nearly universally in political communication effects research – asks subjects to simply identify if they consider themselves a member of a political party and then rate whether that identity is “strong” or “weak,” and for Independents, “leaning” towards one party or the other. The objective of this chapter is to directly test the effectiveness of the PSIM compared to PID in media effects. The questions that inform my hypotheses are: Is PSIM distinct from PID in predicting and/or moderating media effects? Does PSIM outperform PID? And what are the nature of effects associated with PSIM?

Based on my review of the literature in psychology, political science, and communication, combined with the results reported in Chapter 2, it is my belief that strength of partisanship operationalized in line with SIT will be a stronger predictor of media effects and attitudes about the media, and stronger moderator of effects, than the traditional measure of PID. I test this prediction using the data from a two-wave survey collected during the 2020 U.S. presidential election on three media effects outcomes prevalent in political communication research. In short, I will examine the impact of PSIM compared to PID on three highly salient

phenomena in the study of current political communication: hostile media effect, selective exposure behavior, and motivated reasoning.

The remainder of this chapter proceeds as follows. First, I review relevant literature and existing evidence of these three media effects as predicted or moderated by partisanship. I then review additional work that I believe add indirect evidence of deeper group-identity dynamics at play. To test the hostile media effect, I estimate straightforward OLS regression to evaluate the predictive power of PSIM versus PID. For selective exposure, I estimate models using PSIM and PID to predict the outcome of a simple selective exposure experiment in which respondents are asked to choose between positive and negative news headlines about the two front-running presidential candidates. To examine motivated reasoning, I measure trust in a negative compared to a neutral news story about respondents' in-party candidates, using a simple media story exposure experiment. As will be discussed further below, perceptions of credibility of counter-attitudinal information have been a useful indication of motivated information processing in past work. In this final analysis, PSIM and PID are tested as moderators of the impact of the exposure condition on trust.

Overall, I find evidence that PSIM is more strongly predictive than PID of hostile media effects, selective exposure and motivated reasoning. I then discuss how this evidence not only justifies further testing of my proposed partisan social identity measure, but also suggests the advantages of using Social Identity Theory to improve our understanding of the effects of media content in political contexts where partisan identity comes under threat (i.e., elections, impeachment, scandal, and so on).



## Partisanship in Political Media Effects Research

### *Hostile Media Effect*

The “hostile media effect” (HME) occurs when people perceive information as biased against their beliefs. It is a unique phenomenon in communication studies because rather than being a direct effect of media on an attitude, it is an *attitude about media* that is predicted by systematic bias in human processing. Namely, the standard baseline human assumption that our own views or beliefs are correct compared to opposing views and beliefs. Thus, the effect is predicted by a combination of the subject matter triggering bias and the extent of the bias triggered. Subsequently, though, HME has the potential influence other communication effects as well: “hostile media perceptions can precipitate media effects by setting in motion a series of beliefs, attitudes and behaviors” (Perloff, 2015, 703).

HME was originally introduced by measuring people’s perceptions of bias of information at the “story-level.” Early research found that when people with opposing beliefs about a topic or issue were exposed to the same exact piece of information about that topic, *both groups* reported the information as being biased against their point of view. Over time, it has evolved into various other forms, however. For example, scholars have examined hostile media effect in evaluations of entire media outlets (e.g., Coe et al., 2008; Kelly, 2019); scholars have examined general hostility towards the mainstream “media” as an institution (e.g., Weeks et al., 2019; Barnidge et al., 2020); and most relevant to this project, scholars have looked at political party identity as a predictor of hostile information perceptions (e.g., Reid, 2012; Lin et al., 2016). (There are also many meta-analyses and full literature reviews that trace the evolution of this effect and the various conditions under which it has been studied, see, Hansen & Kim, 2011; Feldman, 2014; Perloff, 2015; Gunther, 2017.) The test of hostile media effect I focus on in this chapter best

aligns Weeks et al. (2019) and Barnidge et al.'s (2020) variant, where PSIM and PID, specifically, are tested as predictors of the perception that the *media in general* is biased against a partisan's political group.

Social Identity Theory and cognitive dissonance are very present in the literature on HME. SIT is frequently used to explore the psychological mechanisms through which this biased information processing takes place. The theoretical arguments I laid out in Chapter 1 are almost perfectly aligned with this work. Hartmann & Tanis (2013), for example, highlight how SIT suggests that people are motivated to maintain a positive perception of the group they identify with. This positive perception of the group is critical to positive perception of the self, since the group identity and the self are psychologically tied. "In the context of the HME, group members may be motivated to see that their ingroup occupies a superior *moral* or *ideological* position in a conflict. However, arguments or information provided in the mass media may challenge the ingroup's ideological or moral legitimacy, and, thus, the positive distinctiveness of the group" (Hartmann & Tanis, 2013, 536). In this sense, the media "may pose a symbolic threat to their ingroup" (537) that then can bring about feelings of discomfort and internal conflict in efforts to maintain a positive perception of the self. Thus, when a threat of this kind brings about cognitive dissonance, one might expect behavior such as questioning the bias of said media, (i.e., seeing the information as biased against your group) as way to cope. Hartmann & Tanis (2013) find that stronger group attachment predicts stronger perceptions of hostile media bias.

Hartmann & Tanis (2013) are not the only scholars to connect hostile media effect and SIT. And although, as I argue at the end of this section, these scholars have not tested HME with political partisanship *itself* operationalized as a social group attachment, they present compelling evidence that biased perceptions of media and information are linked to identity threat. Hansen

& Kim (2011), for instance, review 34 different HME-related studies and find the strongest effects are those moderated by what they call “involvement” in the topic at hand. In most studies, involvement is conceived as having strongly held attitudes about a particular issue. The strength of those prior attitudes among participants is found to predict stronger perceptions of the information being biased against the participant. Both Gunther et al. (2016) and Lin et al. (2016) provide further evidence of the importance of *degree* of involvement by demonstrating that the more “attachment” respondents reported to the given political issue, the more hostile their perceptions of neutral or counter-attitudinal information and sources. Lin et al. (2016) dives into the SIT perspective even deeper, finding that other group-identity related factors – group status perception, intergroup bias perception and ideology – further amplified HME.

A potential drawback of Hartmann & Tanis (2013), Gunther et al. (2016) and Lin et al.’s (2016) work as it relates to social identity theory, however, is that they all use strength of attitude about a specific issue as the measure of “group attachment” instead of attachment to an actual social group (i.e., political parties). For example, Hartmann and Tanis use pro-choice versus pro-life attitudes, and Gunther et al. use strength of attitudes about pro-evolution teaching versus teaching alternatives to evolution as their measures. All of this compelling work is thus limited to very specific political issues; and tests of the theory hinge on measures that do not directly capture partisanship, or partisan social identity strength.

That said, there are some scholars who explore HME and partisanship more directly, finding strong evidence of the connection between the two. Eveland & Shah (2003) demonstrate that the degree of strength of the categorical measure of PID predicted increased perceived bias of the news in general. Furthermore, Reid (2012) replicates Eveland and Shah’s results but further shows that when partisan identity was made salient (evoked experimentally) and when

the information came from an out-group affiliated source, HME was amplified. Finally, Ladd (2010) discovers that participants reported lower feelings of favorability towards the media when exposed to their political party leadership criticizing the coverage of the in-party presidential candidate, compared to exposure calling the media critical of all politicians. Hence, general perceptions of the media being “negative” did not elicit increased HME as much as an in-party cue from leadership (this notion is further supported by Arceneaux et al., 2012).

Another way to get a sense of the relationship between hostile media effects, partisanship and social identity attachment (albeit indirectly) is through evidence of the affective nature of HME. One of the central features of social group attachment, after all, is its affective/emotional nature. Even when partisanship is measured via PID’s simple strength categories, there is evidence that affect, and emotion, are present in the hostile media effect process. Matthes (2013) finds that partisans’ emotional reactions to information – measured both as general emotional arousal and as the experience of concrete emotions like anger, enthusiasm and fear – predict HME above and beyond controls for cognitive involvement, such as attitude certainty, importance and need for cognition. Arpan & Nabi (2011) report that partisans who responded with anger to counter-attitudinal news formed more biased judgements of news, and that increased anger led to greater criticism of the reporter and additional pro-attitudinal information seeking behavior. Similarly, Weeks et al. (2019) look at hostile media perceptions on social media and show that “attention to politicians’ social feeds during the 2016 U.S. presidential election is indirectly related to perceptions of media bias through *anger* at the opposed presidential candidate and *enthusiasm* for the supported one [emphasis added]” (287). This evidence suggests that biased perceptions of media or information are not merely a cognitive evaluation, but rather the result of an emotionally eliciting process in line with SIT.

Much of this literature calls on SIT theory as the foundation for understanding the psychological processing that underpins hostile media effect. Strikingly, however, there appears to be very little work in which partisanship is measured that way. Hartmann & Tanis (2013) appear to be the closest, using 14 questions from Leach et al. (2008) adapted to measuring attachment to “pro-choice” or “pro-life” attitudes, though, as opposed to an actual social group. I believe Eveland & Shah (2003) and Reid (2012)’s results most clearly present an opportunity to examine hostile media effect via a measure of partisan social identity that more deeply considers the *degree* of attachment to those groups. In summary, I predict that:

**Hypothesis 1:** PSIM will be a stronger predictor of hostile media effect than PID.

### *Selective Exposure*

The idea that people tend to select information that aligns with their currently held beliefs was first explored in the 1960’s. At the time, there was only inconsistent support for the theory (e.g., see Freedman and Spear’s work in the period). Studying the phenomenon gained popularity again decades later as shifts in the media landscape offered audiences more choice and control over what they consumed. During this period, politics gained popularity as lens through which selective exposure was studied. After all, choosing information in line with a person’s “beliefs” was easy to test via politically related topics that people would likely have attitudes or opinions about. In Stroud’s (2008) review of the field, she highlights that variety in the size and consistency of effects are what continued to fuel debate on the prevalence (or even existence: i.e., Kinder, 2003; Zaller, 1992) of selective exposure behavior. Stroud argues that this conflict, in part, is the result of the “diversity of topics that have been studied” and asserts that “Political topics...may be particularly likely to inspire selective exposure” (344).

The work done by Stroud (2008, 2010), Iyengar & Hahn (2009), and Garrett (2009) revitalized the theory of selective exposure in communication research, particularly as a phenomenon relevant to partisan politics in the U.S. Using the traditional measure of partisanship as a five-category scale (strong/not strong or leaning/neither), Stroud's work demonstrates that stronger partisans were more likely to report selecting news from politically congenial media outlets or from outlets that more often supported their party's candidate for president during the 2004 election. She further finds that partisan selective exposure behavior (i.e., consuming news from partisan congenial outlets) increased over the course of the 2004 campaign, regardless of medium. Stroud (2010) follows with evidence showing that polarizing attitudes can both lead to selective exposure and be the consequence of selective exposure behaviors, but there was stronger evidence of the latter. Thus, partisans who engaged in more selective exposure behaviors were more likely to hold polarized attitudes. Iyengar & Hahn (2009) replicate these results, both for political issues that are highly controversial and for "softer" subjects (i.e., regardless of the nature of the content). Selective exposure behavior was amplified for partisans with strong political interest as well. And finally, Garrett (2009) finds strong evidence of partisan selective exposure at the story-level, where opinion-reinforcing stories better predicted selection than opinion-challenging stories.

This work makes clear that the changed media landscape has introduced the opportunities needed for selective exposure behavior to (a) be more prevalent and (b) be better measured. Consumer-based selection of media source and content is now deeply baked into the structure of the media industry in a way it wasn't before. This is especially so where politics is concerned, as now there are channels and shows intentionally devoted to a particular partisan point of view. Rodriguez et al. (2017), for example, find that selective exposure increased over the 2000 – 2012

period, particularly for conservatives (most pronounced for “very conservative” identifiers). But that’s not to say that people are locked in “echo chambers;” particularly since the expansion of choice has also allowed citizens to opt out of political news altogether (Prior, 2007) and in the online environment where the quantity of choices expands even further, Facebook news sites’ audiences tend to be politically diverse (Nelson & Webster, 2017). Kim & Lu (2020) also simulate an iOS news app where participants could freely select news stories and find that while partisans preferred stories from pro-attitudinal sources, they also selected from counter-attitudinal sources about 20% of the time.

In sum, although selective exposure may not be ubiquitous, the evidence to date does makes clear that selective exposure behaviors are present among political partisans. Furthermore, recent work has started to situate these behaviors more in line with Social Identity Theory. Indeed, SIT may be a useful tool in understanding variation in selective exposure outcomes. Levendusky (2013) argues that partisan media “triggers” partisan identity, by creating identity salience, exacerbating group contrast and conflict, and reinforcing partisan attitudes. He contends that partisan media is thus especially persuasive and found that partisans rate these sources as more credible. Interestingly, selecting like-minded media exposure had little impact on in-party attitudes (likely at an already too high threshold) but in contrast predicted lower levels of affect towards the opposing party group. The degree of strength of partisan identification may matter as well. Kim & Lu (2020)’s evidence of selective exposure is only present for strong identifiers, where weak identifiers and leaners showed little preference for pro-attitudinal sources over mainstream sources in mobile news consumption.

Kim & Kim (2021) more directly consider SIT as a way to understand inconsistency in source-level selective exposure patterns among partisans. They find that even when general

media diets are relatively balanced, partisans vary their attentiveness and consumption in response to whether a *news event* is congenial to their party. This is not just an outlet-based phenomenon, then, but contingent on contexts that make identities salient (what they call *temporal selective exposure*). By applying SIT, Kim and Kim argue, “one overlooked way in which partisans might minimize cognitive dissonance: by choosing not to pay as much attention to politics when their party is losing...It is more plausible and much simpler for partisans to avoid cognitive dissonance by deciding when to consume news rather than by purposefully picking media sources that match their dispositions” (no page number, online only). Playing into the affective nature of social identity attachment, Song (2017) analyzes the 2012 American National Election Studies data and finds that fear, anger and enthusiasm all significantly increased pro-attitudinal news exposure and anger (alone) decreased counter-attitudinal news exposure. Finally, Peterson et al. (2021)’s show that politically congenial election-related coverage during the 2016 presidential election was strongly predicted by partisanship, but not driven by race, gender or education. Thus, it was the attachment to the political identity that truly drove the behavior.

Existing work on selective exposure has significantly advanced, particularly within the context of political news consumption. It has not, however, completely resolved concerns over the diversity (or inconsistency) of effects. Ha et al. (2018), for example, find that conservatives/Republicans practiced more selective exposure behaviors while liberals/Democrats tended to have more balanced news diets (see also, Iyengar et al. 2008). Garrett & Stroud (2014) demonstrate that selective *avoidance* of counter-attitudinal information was only significant for Republicans. And Messing & Westwood (2014) show that information popularity (“likes”) can trump partisan media source cues. In all the work highlighted above, partisanship is



operationalized using the traditional categorical measure. Could partisanship measured as social identity attachment help better understand these differences?

I believe so. While there are clearly variations in the conditions in which selective exposure behavior occurs and for whom (e.g., outlet vs. story, Republican vs. Democrat), *strength* of attachment to partisanship – as traditionally measured – or political issue appears to be the most consistent predictor of selective media consumption in the literature. Partisanship operationalized as strength of group identity attachment (PSIM) provides a richer (and arguably more accurate) measure of the nuances of partisan group identification directly rooted in SIT, thus potentially improving its potency and reliability in predicting selective exposure.

Social Identity Theory suggests that people with strong social group identity attachment engage in information processing and behavior that aims at maintaining a positive perception of the group in contrast to the out-group. Using this framework, I expect partisans high in PSIM to be drawn to media messages that bolster positive feelings about the in-group, and conversely, information that reflects poorly on the out-group. I conduct a simple selective exposure experiment to test these assertions (explained in detail in the methodology) where respondents are asked to select between positive and negative news headlines about the two front-running presidential candidates in the 2020 election. I believe that:

**Hypothesis 2a:** PSIM (and PID) will predict selection of positive news headlines about the in-party candidate.

**Hypothesis 2b:** PSIM (and PID) will predict selection of negative news headlines about the out-party candidate.

**Hypothesis 3:** PSIM will be a stronger predictor of selective exposure behavior than PID.

## *Motivated Reasoning*

Motivated reasoning is a theory about the psychological process through which people reason or make sense of information. It is argued that people process information in different (often biased) ways depending on their motivation or goals. Kunda (1990) notes that “motivation may affect reasoning through reliance on a biased set of cognitive processes: strategies for assessing, constructing and evaluating beliefs” (480). She outlines two types of reasoning goals based on current evidence at the time and theories on cognitive dissonance: accuracy goals and directional goals.

The motivation to arrive at an *accurate* conclusion when consuming information shapes the reasoning process whereby people “expend more cognitive effort on issue-related reasoning, attend to relevant information more carefully, and process it more deeply, often using more complex rules” (Kunda, 1990, 481). She argues that accuracy motivation leads to less stereotyping, less primacy effect, less anchoring and less attribution error. However, accuracy is most prevalent when primed to participants experimentally before an exposure – thus bringing into question whether the motivation to be accurate is a common or natural human process.

*Directional* motivation is argued to be more common in the sense that it is naturally prompted by information around us (rather needing to be primed by researchers). Directional motivation has a specific, desired outcome or intention. Kunda explains this process as: “people motivated to arrive at a particular conclusion attempt to be rational and to construct a justification of their desired conclusion that would persuade a dispassionate observer” (482-3). Thus, when exposed to information, people will be selective of what parts to consider, and their assessment of those parts will be determined by what best helps them reach the intended goal (Epley & Gilovich, 2016). This biased processing often occurs unconsciously and in fact, people

often perceive they are being accurate when directional is occurring – what scholars describe as “illusion of objectivity.”

The discomfort brought about by cognitive dissonance is suggested to be a trigger of directional motivated reasoning (e.g., Festinger, 1957). Dissonance is a psychological reaction that can be activated by perceptions of contradiction or inconsistency within the self. A threat to positive feelings about the self is a potent way for dissonance to have a tangible effect on processing or attitudes (e.g., Stone & Cooper, 2001). Dissonance theorized in this way is an effort in self-preservation or “self-affirmation” (e.g., Steele & Liu, 1983).

SIT is deeply connected to notions of cognitive dissonance (and motivated reasoning). Perception of threat to the group’s status, resources or reputation has the potential to reflect negatively on the individual strongly attached to that group, which subsequently creates discomfort. Cognitive dissonance likely shapes the individual’s reaction to the threat (e.g., Gawronski, 2012), motivating her or him to warp interpretations of the information or evaluations of its credibility (e.g., Kraft et al., 2015) towards positive self- and group-preservation. Motivated reasoning of this kind involves biased processing from recall and construction of an individuals’ own traits, attitudes and behaviors to drumming up prior knowledge that constrains information processing and serves as an anchor for interpreting new information. An actual change in attitude as a result of dissonance, then, would only occur if there’s a desirable outcome to do so, that is in line with in-group cues (e.g., Bayes et al., 2020) or strong enough to counteract a self-preservation motivation (e.g., “affective tipping point,” Redlawsk et al., 2010).

Furthermore, Kunda (1990) makes clear that “the evidence that counter attitudinal behaviors will create dissonance only [occurs] when they involve a threat to the self is

considerable and compelling” (484 – 485). Leeper & Slothuus (2014) also assert that particular individual predispositions influence behaviors or outcomes as a result of directional motivated reasoning if dissonance is provoked by a relevant context. Specifically, they argue that *political partisan conflict* is a necessary condition for dissonance and motivated reasoning to be predicted by partisanship, as “parties mobilize citizens and tell them how they should understand the political choices before them and, by implication, what political predispositions should be applied and how” (133).

Motivated reasoning has often been studied and triggered experimentally by exposing participants to information that is contradictory to their currently held beliefs. However, much recent work uses political partisanship as the marker of pre-established attitude direction. Similar to research on HME and selective exposure, the traditional categorical measure of partisan identification is universally used as the operationalization of political social identity in this literature. Again, despite the limitations of the measure of partisanship, I believe there is ample indirect evidence to support the framing of information-induced motivated reasoning as a function of Social Identity Theory.

Bolsen et al. (2014), for example, find that only under the condition where partisan identities are primed did participants engage in directional motivated processing of information. When subjects were asked to defend their party identity prior to exposure, they shifted their attitudes about the 2007 Energy Act toward the position endorsed by the party. The authors find no changes in attitudes when subjects were primed for accuracy motivations nor when endorsement of the act was described as supported across party lines. Finally, the data shows that partisans spent just as long processing partisan-endorsed information as the information presented in the other conditions, leading the authors to believe that partisanship cues are not

simply “shortcuts” in processing. When exposed to out-right misinformation, Peterson & Iyengar (2021) report “support [for] the motivated reasoning interpretation of misinformation; partisans seek out information with congenial slant and sincerely adopt inaccurate beliefs that cast their party in a favorable light” (133). There are many other examples of work that highlight the role of partisan identification in motivated reasoning across many topics, such information about climate change (e.g., Hart & Nisbet, 2012; Hameleers & van der Meer, 2020), economic trends (e.g., Bisgaard, 2019), conspiracy theories (e.g., Enders & Smallpage, 2019), and in response to presidential debates (e.g., Warner et al., 2020).

That said, not all scholarship points to strength of partisan attachment as the singular driver of political motivated reasoning. Taber & Lodge (2006), for example, present compelling work about the role of “political sophistication” in motivated reasoning processes. They find that respondents who were more knowledgeable about politics (sophistication) and had strong prior attitudes about a given policy (gun control and affirmative action) were more likely to rate congruent arguments as stronger and incongruent arguments as weaker compared to those less sophisticated. Although strength of partisanship was not included in their models, it is likely related to Taber and Lodge’s conceptualization of political sophistication as we often find that partisanship is highly correlated with more interest in and knowledge about politics. In other words, identity may still be the central driver here, but sophistication is a useful tool in predicting motivated reasoning because sophisticates may be able to *more effectively* assess when the in-group is being threatened by new information.

Finally, further evidence of the connection between SIT and motivated reasoning can be found on a physiological level. Physiological research suggests that directional motivated reasoning is a product of affective information processing in political contexts (as one would

expect if group-identities were challenged, based on SIT). Westen et al. (2006) use neural imaging to study partisans during the 2004 U.S. presidential election and find that when participants were exposed to party-threatening information compared to exculpatory information about their party's candidate, different parts of the brain were activated. The threatening information initially triggered negative affective processing. Interestingly, though, "when confronted with information about their candidate that would logically lead them to an emotionally adverse conclusion, partisans arrived at an alternative conclusion" (1955). They observe that participants made efforts to resolve the contradictory information, and that this secondary processing triggered positive affect in the brain. Not only did this demonstrate that threatening information elicited affective responses (in line with SIT), but it also shows that a process of "resolving" the negative feelings occurred and once that motivation was achieved, the brain, in a sense, rewarded the process with feelings of positivity.

The literature on directional motivated reasoning and partisanship is strongly suggestive of the importance of social identity attachment. However, most of the research in this field has focused on traditional measures of party identification (or other related measures such as sophistication). There are situations – such as a study targeting motivated reasoning in reactions to very specific policy issues – where these measures may be sufficient. In the context of political elections, however, when information is likely to provoke more of a threat to group identity status, power and reputation, I believe the measure of psychological attachment to political groups (PSIM) may better explain individual-level variation in directional motivated reasoning.

A common and relatively simple indicator of directional motivated reasoning in the literature is the perception of trustworthiness or assessment of credibility of counter-attitudinal

information. For example, Metzger et al. (2020) find that partisans judge attitude consistent and neutral information as more credible than attitude-challenging information (see also, Clayton et al., 2019). This pattern was replicated for credibility evaluations of sources as well (Robertson, 2021). In this chapter, I test PSIM's relationship to motivated reasoning compared to PID by exposing respondents to either a negative or neutral news story about the two front-running presidential candidates and asking them to evaluate the trustworthiness of the story. A motivated reasoning hypothesis predicts that in the face of information that reflects poorly on the in-group, the stronger the partisan attachment the more likely the respondent will *distrust* the information. Thus:

**Hypothesis 4:** For respondents exposed to a negative story about their in-party candidate, PSIM (and PID) will predict less trust of the story.

**Hypothesis 5:** PSIM will be a stronger predictor of motivated reasoning than PID.

## Methodology

The analyses presented in this chapter will use data from both wave 1 (distributed August – September 2020) and wave 2 (distributed October – election day 2020) of the survey described in Chapter 3. Hostile media perceptions and selective exposure will focus on data from wave 1, while evaluations of story trust will use data collected post-exposure experiment from wave 2. The response rate for wave 2 was about 47%. The sample includes 524 Democrats and 515 Republicans, and no Independents. Independents were not targeted for the second wave of the survey because there were so few to begin with, and because the experiment in the second wave was designed to elicit in-party versus out-party reaction (thus, having a party identity is a necessary prior). Overall, the distributions of demographics map well onto those from the first

wave. The returning respondents were roughly even in terms of gender for Democrats, with about 52% identifying as female, while Republicans identifying as female made up about 44% of the returning sample. The Democrat lean towards more female identifiers compared to Republicans is in line with the skew in wave 1. Distribution of political interest remained relatively the same with 80% of Democrats and 82% of Republicans reported as being somewhat, very or extremely interested in politics. The second wave similarly skews slightly educated with about 65% of the returning sample reporting some college education. In terms of race, the sample leans slightly more towards respondents who identify as white (e.g., 14% identified as Black in wave 1 and about 10% identify as Black in wave 2). Finally, age remained relatively normally distributed between the ages of 18 through 85 and older, with the largest group of respondents falling in the “45 – 55” category at 22% of the total sample.

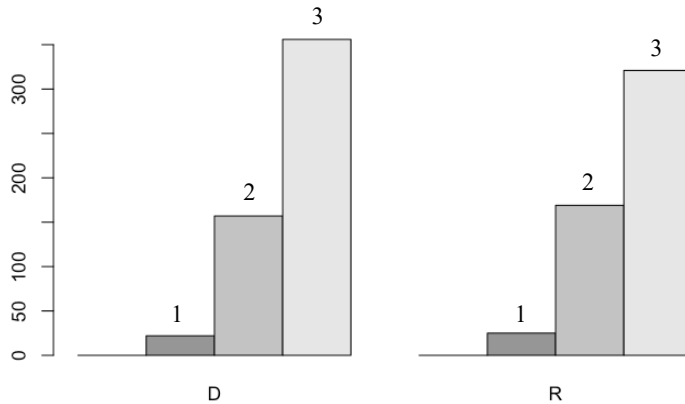
#### *Independent Variables: PSIM and PID*

As outlined in the previous chapter, PID is measured in wave 1 using the traditional categorical measure of partisanship where respondents are asked, “Generally speaking, do you usually think of yourself as a Republican, a Democrat, an Independent, or what?” followed by “Would you call yourself a strong [Democrat/Republican] or a not very strong [Democrat/Republican]?”. Independents were asked towards which party they lean and incorporated into a seven-point scale (strong/weak/lean/neither). For the purposes of comparing the PSIM measure to PID in identifying the impact of *strength* of political group attachment on media effects, PID was recoded to four categories where 0 represents Independents (thus, there are no respondents with 0 for PID in these analyses), 1 represents leaners, 2 represents weak identifiers and 3 represents strong identifiers (for both Democrats and Republicans combined). Figure 4-1 shows the distribution of this collapsed version of PID strength, with Democrats in



the left panel and Republicans in the right. The distribution of strength of PID leans significantly towards high identifiers for both Democrats and Republicans, similar to the wave 1 sample.

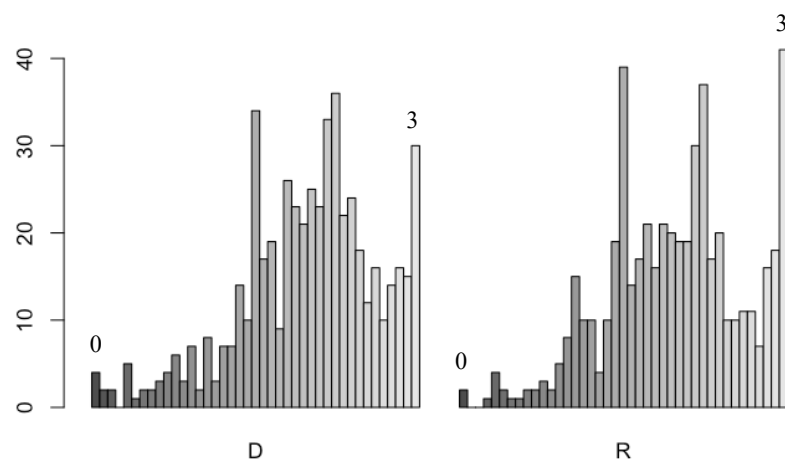
*Figure 4-1: Distribution of re-coded PID in Wave 2*



The measure of partisan social identity attachment (PSIM) used in the following analyses is the battery of the top ten questions from the PSIM measure in Chapter 3 that most strongly load onto the first dimension. The index includes questions from the following theoretical constructs: importance/centrality (three questions), solidarity/connectedness (three questions), affect/attachment (one question), behavior (one question) and common fate (two questions). Recall that these top ten questions were correlated with all 37 questions used to measure PSIM at  $r = 0.949$ . The ten PSIM questions were measured using a five-point agree/disagree scale, with the scores originally added together resulting in a combined numeric scale where -20 is no psychological attachment to the group and 20 is extremely strong psychological attachment to the group. PSIM in this chapter was then re-scaled to match the same range of PID (0 – 3). Thus a 0 in PSIM indicates no psychological attachment to the group and 3 represents extremely strong psychological attachment, allowing for direct comparisons of the coefficients in the OLS models. Figure 4-2 shows the distribution of PSIM among second-wave respondents, with Democrats in the left panel and Republicans in the right. The distribution of PSIM is slightly

skewed towards strong attachment for both Democrats and Republicans, similar to the full wave 1 sample, though with more variation in between.

*Figure 4-2: Distribution of re-coded PSIM in Wave 2*



*Dependent Variable: Hostile Media Effect, Wave 1*

After answering the partisan social identity questions and general questions about media use, respondents in the first wave were asked to evaluate how biased they considered the media (in general) was against their political party’s candidate. Weeks et al. (2019) highlight that “there is little consistency in the literature on how to operationalize hostile media perceptions” (383). The authors present a novel measure designed to capture general feelings about the “lack of media neutrality and fairness” by mainstream outlets towards candidates during a presidential election. The context in which Weeks and authors deployed this measure (on a survey during the 2016 U.S. presidential election) was identical to the context in which my survey was deployed, thus I adopt their method for measuring hostile media effect. The respondents were asked, “How likely is it that the mainstream media try to unfairly influence the election against

[Democratic/Republican] candidates?” Partisans were asked only about their in-party, and the responses were along a five-point scale (0 = “not at all” to 4 = “extremely”).

*Dependent Variable: Selective Exposure Experiment, Wave 1*

Wave 1 also included a selective exposure experiment. After being asked about hostile media perceptions, respondents were presented with four headlines and prompted to select one that they were most interested in reading about President Trump. Then asked to do the same with headlines about President Biden. The order of exposure to Biden versus Trump headlines was randomized across all respondents. Selection of headlines has proven to be a reliable measure of selective exposure behavior in recent political communication research (see e.g., Knobloch-Westerwick et al., 2005; Kim et al., 2016; Powell et al., 2019; Kim & Lu, 2020). Bachleda et al. (2020) argue that a benefit of this approach lies in its (a) similarity to natural news consumption environments, particularly in online and mobile news and (b) because it is very easy to deploy in time and space-limited survey research.

For the purposes of exploring the usefulness of an SIT-focused measure of partisanship, the experiment focused on respondents choosing between negative or positive headlines about the two candidates. Negative headlines about the respondents’ own party candidate present a potential threat to positive group identity perceptions while positive headlines, one would expect, could bolster those perceptions. Note that respondents were presented with four headlines in total, two positive and two negative. Including more than one positive and negative option attempted to account for any particular headline simply being more interesting (or uninteresting) than another. There was also careful consideration in making the Trump and Biden headlines as similar in topic as possible. The individual headline order was randomized. Table 4-1 lists the headline options along with the percent of respondents who selected those headlines. Note that

all headline selection proportions range from 32% at the highest to 19% at the lowest, indicating that no one single headline, nor one sentiment category, captured more than a third of respondents' attention. Given this relatively even distribution, selective exposure was converted to a binary "selected positive Trump/Biden headline" variable where 1 indicates a positive headline was selected and 0 indicates a negative headline was selected.

*Table 4-1: Selective Exposure Headline Stimulus and Distributions*

<b>Candidate</b>	<b>Headline Sentiment</b>	<b>Headline</b>	<b>Topic</b>	<b>Selection Rate</b>
Trump	Negative	Donald Trump Could be in Trouble with Youngest Generation of GOP	Trouble in polls	32%
Trump	Negative	Trump retweets quote from fascist dictator Mussolini in latest Twitter blunder	Public blunder	19%
Trump	Positive	Trump, in Mount Rushmore address, calls on Americans to Rise Up	Inspiration	21%
Trump	Positive	Trump Executive Order Improves Child Welfare System	Positive policy	28%
Biden	Negative	Biden Struggling in Polls with Young Black Voters	Trouble in polls	27%
Biden	Negative	Biden says 'poor kids' just as bright as 'white kids' in latest gaffe	Public blunder	23%
Biden	Positive	Biden to 2020 Graduates: Build America Better Tomorrow than it is Today	Inspiration	29%
Biden	Positive	How Biden's Informal Diplomacy Improves U.S. Foreign Relations	Positive policy	21%

#### *Experimental Treatment: Negative Media Content Exposure, Wave 2*

The second wave of the survey included an experiment designed to test partisan reactions to negative versus neutral media coverage of their in-party presidential candidate. This experiment was used as the manipulation for the test of motivated reasoning. The subjects were first randomly assigned to one of two negative stories or a neutral story about the in-party presidential candidate. Immediately following the exposure, respondents were asked to rate how they feel about the in-party candidate using the 0 – 100 scale feeling thermometer, to evaluate their trust of the information they just read and to report if this information was new to them or if they had read about it before. Next, respondents were randomly assigned to one of two negative

stories or a neutral story about the out-party candidate, immediately followed by the same three questions.

Note that the objective of this project is to test how partisan identity attachment affects responses to potential group threat. Thus, the stimulus only focuses on threat-provoking negative media coverage of the candidates compared to neutral coverage, with no “positive coverage” stimulus. Based on the theory and evidence I have reviewed, I believe that positive coverage of the in-party candidate would likely result in maintenance of current (already high) positive attitudes towards the in-party candidates (as was suggested in the results in Chapter 2, as well). While there could be interesting results to explore if partisans were exposed to positive stories about *out-party* candidates, I opted to leave this for future research given the space limitations of the survey and concern about breaking up an already small returning sample into additional conditions.

What constitutes a “negative” news story about a presidential candidate is open for debate and interpretation. In Chapter 2, for example, I used a relatively conservative and general bag-of-words count of negative tone in media coverage as my measure of “negative press” (Lexicoder Sentiment Dictionary created by Young & Soroka, 2012). This decision was motivated by needing a reliable tool that could be deployed on a large body of text spanning multiple decades. In this experiment, “negativity” in the news stories is defined as a potential group threat, as laid out in Social Identity Theory. Decisions about the stimulus were equally motivated by an interest in keeping the stimulus as simple, straightforward and realistic as possible. Thus, there is no policy mentioned in any of the stories (as not to conflict with strength of attitude about an issue/counter-attitudinal perceptions) nor is horse-race coverage nor polling (as not to conflict with potential particularities in attitudes about these types of stories). Because

the survey was conducted during the actual presidential election, I also selected stories that were true in an effort increase the believability of the content and to avoid spreading potential misinformation about real candidates. Two negative stories (compared to one neutral) were selected for each candidate to control, again, for any one particular story being especially interesting (or uninteresting) to respondents.

The literature reviewed on SIT and media effects above underscores the importance of the information eliciting a potentially negative or damaging perception of the in-group. It is in the face of information that could hurt the positive reputation or perception of the in-group that people with strong group attachment become uncomfortable and shift into self/group-preservation processing. I selected four stories in which the presidential candidates made a public blunder that I believe had the potential to reflect poorly on their reputations (and that of the parties). All four stories report on what President Trump and then candidate Biden said themselves, rather than an external analysis of their policies or behaviors by a reporter, for example. By keeping all of them the same exact type (public blunder), I aimed for more control and consistency in the stimulus. Similarly, the neutral stories are as unemotional as possible, simply reporting on each candidate making a campaign visit with his family. Full stories used in the experimental stimulus are listed in Appendix C (Figures C1 – C3), below is a brief summary:

**Trump negative story 1:** Trump quotes fascist dictator, Mussolini, on Twitter

**Trump negative story 2:** Trump confuses 9/11 with 7 Eleven during campaign speech

**Trump neutral story:** Trump heads to Michigan on the campaign trail

**Biden negative story 1:** Biden says racial blunder during campaign speech in Iowa

**Biden negative story 2:** Biden mistakes running for Senate instead of President

**Biden neutral story:** Biden heads to Pennsylvania and Ohio on the campaign trail

### *Dependent Variable: In-party Story Trust (Motivated Reasoning), Wave 2*

As mentioned above, respondents in wave 2 are first exposed to a negative or neutral story about their in-party candidate are tasked immediately following to rate how much they trusted the story they read. The question asked: “To what extent do you **trust** the news story you read above about [former Vice President Joe Biden/President Donald Trump]?” The responses are categorized as a five-point trust/distrust scale (strongly/somewhat/neither). The results for Democrats evaluating a story about Biden and Republicans evaluating a story about Trump were then collapsed into one variable: *in-party trust*. The five-point scale was made numeric where -2 represents strongly distrust, 0 represents neither trust nor distrust and 2 represents strongly trust. In-party trust captures all respondents’ trust evaluations of the in-party story exposure and is used as the dependent variable representing motivated reasoning in the analyses.

### *Control Variables*

The models discussed below report OLS regression results without control variables. Each model, however, has been tested with a full battery of demographic and political- or media-related control variables. As will be discussed below, introducing controls into the models do not change the significance, signs nor size of coefficients – thus the models are listed in Appendix C (Tables C1, and C5 – C7). The demographic variables used as controls were measured in the first wave and include gender identification as a binary (female/not female), some college attendance as binary (university/no university), age as a numeric conversion (0 – 8) of the nine age categories starting with under 18 to 85 and older at increments of about 10 years, and race as a

binary of identifying as Black or African America/not Black<sup>3</sup>. Political interest was also included as a control, which was measured as a numeric five-point scale ranging from 0 representing “not at all interested” to 4 representing “extremely interested.” The final control included in the models was general weekly news consumption. Respondents were asked, “Thinking about a typical week, about how many days of a week do you watch or read the news? This can be in newspapers, on television, on the radio, online, on social media, etc.” and prompted to select from 0 to 7. Next, if the respondents selected any number above 0, they were asked, “On days that you watch or read the news, about how much time do you spend doing this?” and prompted to select from four categories: “Less than 30 minutes,” “1 hour or less,” “1 – 2 hours,” or “3 hours or more.” Finally, these two questions were combined into one *media use* measure where the days (0 – 7) were multiplied by the hours (0.5 – 3) to create one numeric scale with 0 being absolutely no news consumption to 21 representing three hours or more, seven days a week.

## Results

### *Hostile Media Effect*

The first analysis will compare the effects of PSIM and PID on HME. Table 4-2 shows results from three OLS regression models, first regressing HME on PID alone, then PSIM alone, and finally PID and PSIM together. Results support hypothesis 1. The PSIM measure is indeed a stronger predictor of HME than is PID. On its own, PID significantly predicts hostile media

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<sup>3</sup> I ran multiple variations of these models adjusting for different measures of race. From including all eight race categories to White/Black/Hispanic/Other. None of the adjustments affected the results. This, combined with the fact that this project does not focus on comparisons between PSIM and racial identity, the binary iteration was included in the final Appendix models for simplicity. Exploring the potential connections between PSIM and race would be an interesting pursuit in future work.



effects, accounting for about 2% of the variance. PSIM similarly predicts hostile media effects, although the PSIM coefficient is nearly double the magnitude of the PID coefficient. (Recall that they are scaled similarly, and although PSIM is a much more nuanced interval-level measure, the standard deviations are very similar: 0.65 for PID and 0.64 for PSIM.) PSIM also explains a far greater proportion of the variance than does PID.

When both PID and PSIM are included in the same model, PID is entirely insignificant. PSIM remains highly significant, however. As PSIM increases, so does HME. This could be, in part, due to the fact that 10-item PSIM naturally has less random measurement error than a one-item measure. That said, this model, again, accounts for about 10% of the variance HME, and all of that variance is explained by PSIM alone. These results hold in the context of several robustness checks: Appendix Table C1 replicates the results controlling for political interest, gender, education, race, age and weekly media consumption; Appendix Table C2 reveals similar predictive power of PSIM over PID when looking at Democrats and Republicans separately.

*Table 4-2: Hostile Media Effect, All Respondents, Wave 1*

	<i>Dependent variable:</i>		
		HME	
	(1)	(2)	(3)
PID	0.304*** (0.046)		-0.041 (0.050)
PSIM		0.599*** (0.038)	0.616*** (0.044)
Constant	1.733*** (0.123)	1.316*** (0.082)	1.388*** (0.121)
Observations	2,321	2,321	2,321
R <sup>2</sup>	0.019	0.095	0.095

*Note:* \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

There is, in sum, ample evidence in Table 4-2 that a measure of partisanship that is more closely aligned with partisan *identity attachment* offers better explanatory power for the hostile media effect than does the standard measure of PID.

### *Selective Exposure*

Hypotheses 2a and 2b suggest that if SIT dynamics are at play, PSIM (and PID) will predict selection of more positive headlines about the in-group candidate and selection of more negative headlines about the outgroup. Selective exposure in these models is captured using a binary variable where 0 represents selecting a negative headline and 1 represents selecting a positive headline. Thus, positive coefficients thus represent increased selection of positive headlines.

As an initial manipulation check, I find that 74% of strong Republicans selected a *positive* Trump headline, followed by 60% of moderate Republicans. Conversely, 74% of strong Democrats selected a *negative* Trump headline, followed by 62% of moderate Democrats. An identical pattern exists in the selection of Biden headlines, where 70% of strong Democrats selected positive, followed by 63% of moderate Democrats, and 72% of strong Republicans selected negative Biden headlines, followed by 64% of moderate Republicans. It is clear that partisans are more interested in reading positive stories about the in-group candidate and negative stories about the out-group candidate.

More detailed tests of hypotheses 2a and 2b are offered in Tables 4-3 and 4-4. Table 4-3 shows six models – three for Republican respondents and three for Democrat respondents – where PSIM and PID are used to predict selection of positive headlines about President Trump and President Biden. The first and third models look at the predictive power of PID alone; the second and fourth models test the predictive power of PSIM alone; and the third and sixth

models include PID and PSIM together. I use basic OLS regression for these models to enable meaningful interpretation of the R-squared coefficients. I ran the models in Tables 4-3 and 4-4 using binomial logit regression as well, however, and the results are nearly identical to OLS (see Appendix Tables C3 and C4). The measures of model fit using logit regression (AIC) also mirror those revealed by the R-squared measures.

Tables 4-3 and 4-4 provide evidence to support hypotheses 2a and 2b. The coefficients for PSIM and PID in predicting in-party headlines are all positive (2a), and the coefficients predicting out-party headline selection are all negative (2b). Furthermore, hypothesis 3 posits that PSIM will be a stronger predictor of selective exposure behavior than PID. This hypothesis is partially supported. Starting with in-party headline selection, for both Democrats and Republicans, PSIM and PID are highly significant in predicting positive headline selection – statistically speaking they are no different in magnitude of the effect – but PSIM accounts for about twice as much variance explained (although the R-squared sizes are rather small, where PID accounts for about 1% (R) or 0.5% (D) of variance and PSIM accounts for just over 2% of the variance). For Republicans, the sizes of the coefficients are also about the same, but for Democrats the coefficient for PSIM is slightly larger. When PID and PSIM are included together in the model, PID loses significance compared to PSIM which remains highly significant for Democrats. For Republicans, both PID and PSIM remain significant in the model, though PSIM slightly more so, and with a slightly larger coefficient.

Table 4-3: Selective Exposure of Trump Headlines by Party, Wave 1

<i>Dependent variable:</i>						
Selecting Positive Trump Headline						
	Republicans			Democrats		
PID	0.112*** (0.024)		0.064** (0.028)	-0.090*** (0.024)		-0.036 (0.027)
PSIM		0.110*** (0.021)	0.082*** (0.024)		-0.118*** (0.021)	-0.103*** (0.024)
Constant	0.395*** (0.064)	0.464*** (0.044)	0.355*** (0.065)	0.534*** (0.064)	0.535*** (0.044)	0.598*** (0.065)
Observations	1,131	1,131	1,131	1,190	1,190	1,190
R <sup>2</sup>	0.019	0.024	0.029	0.012	0.026	0.027

*Note:* \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

Table 4-4: Selective Exposure of Biden Headlines by Party, Wave 1

<i>Dependent variable:</i>						
Selecting Positive Biden Headline						
	Republicans			Democrats		
PID	-0.089*** (0.024)		-0.060** (0.028)	0.058** (0.024)		0.020 (0.028)
PSIM		-0.075*** (0.021)	-0.049** (0.024)		0.081*** (0.022)	0.073*** (0.025)
Constant	0.547*** (0.065)	0.468*** (0.045)	0.571*** (0.066)	0.520*** (0.066)	0.509*** (0.046)	0.474*** (0.067)
Observations	1,131	1,131	1,131	1,190	1,190	1,190
R <sup>2</sup>	0.012	0.011	0.015	0.005	0.012	0.012

*Note:* \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

The results for selective exposure behavior when in exposed to out-party headlines is a bit more complex. The findings described above are replicated for Democrats. Both PSIM and PID are highly significant at predicting less positive headline selection in the Trump condition, though PSIM has a larger coefficient and accounts for about twice as much variance (again,

small overall, though: 1.2% compared to 2.6%). When put together, PID loses significance and PSIM remains highly significant. For Republicans selecting out-party headlines, PID and PSIM are both highly significant on their own, however, with PID's coefficient slightly larger. I find the same result when they are modeled together – both remain highly significant with a slightly larger coefficient for PID. Although the results would be clearer in supporting hypothesis 3 if PID were to lose significance in both the combined model for Republicans, the fact that PSIM and PID remain significant still indicates they capture variance relatively independent of one another. Note, the results of the combined models hold up relatively well even when including the full battery of controls (see Appendix C, Tables C5 and C6).

#### *In-Party Trust of Negative vs. Neutral Story Exposure (Motivated Reasoning)*

The next analyses will focus on the data collected in the second wave resulting from the experimental exposure to a negative or neutral news story about the front-running presidential candidates. After the exposure, respondents were asked to evaluate how much they trusted the story they had just read. Hypothesis 4 suggests that PSIM and PID will predict less trust of negative stories about the in-party candidate; and hypothesis 5 predicts that PSIM will explain more variation in trust than PID.

Table 4-5 presents three models. First, in-party story trust is regressed on the exposure condition (binary negative exposure/neutral exposure), PID and the interaction of exposure and PID using basic OLS regression. The second model tests the same using PSIM instead of PID. The final model, in order to test the power of PSIM compared to PID includes both the interaction of PSIM and PID with exposure condition.

It appears that the direct effect of the negative exposure condition on trust is not significant, all the work is being done by a combination of the partisanship variables and/or the

interaction effect. Both PID and PSIM are significant in predicting *increased* trust of the story about the in-party candidate (in the neutral story condition). As hypothesized, however, the interaction between the experimental condition and PSIM suggests *lower* levels of reported trust of negative stories amongst respondents who are high in PSIM compared to the neutral story condition. To be clear, high identifiers who were exposed to a negative (compared to a neutral) story about their own candidate rated that story as *less* trustworthy than the neutral story.

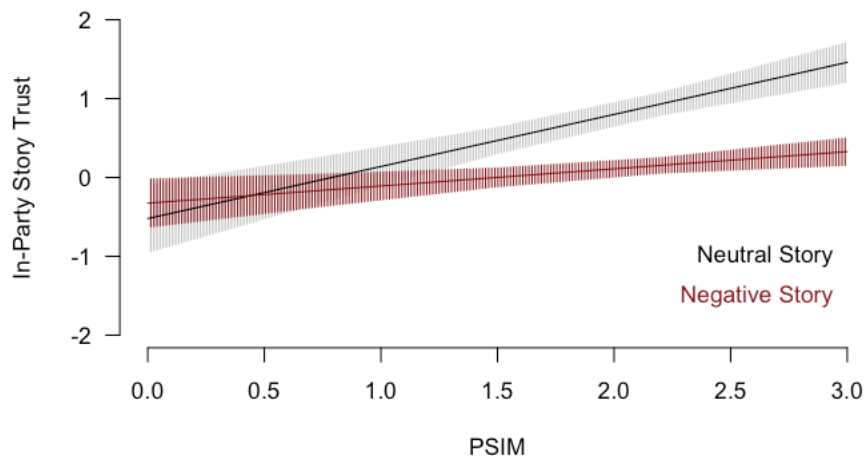
The interaction is illustrated in Figure 4-3. The grey line represents those who were exposed to a neutral story about the in-party candidate, while the red line are the respondents exposed to a negative one. At very low levels of PSIM, the evaluation of trust in the story is about the same between the two conditions (slightly distrusting).

Table 4-5: Trust of In-Party Story, Interaction of Exposure Condition and PSIM/PID

	<i>Dependent variable:</i>		
	In-party Story Trust		
	(1)	(2)	(3)
Negative exposure	0.217 (0.389)	0.196 (0.268)	0.369 (0.391)
PID	0.418*** (0.119)		0.041 (0.138)
Neg exp.*PID	-0.346** (0.147)		-0.100 (0.168)
PSIM		0.660*** (0.105)	0.641*** (0.124)
Neg exp.*PSIM		-0.443*** (0.129)	-0.398*** (0.150)
Constant	-0.296 (0.314)	-0.522** (0.218)	-0.589* (0.315)
Observations	1,039	1,039	1,039
R <sup>2</sup>	0.068	0.098	0.099

Note: \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

Figure 4-3: Trust of In-party Story by Exposure Condition, PSIM



Yet for the strongest identifiers (at high levels of PSIM), the grey and red lines diverge significantly. High identifiers trust a neutral story much more than they trust a negative story. This result is in line with Hypothesis 4. Overall, respondents' trust of the negative story remains roughly the same across varying levels of PSIM. Yet, for stronger identifiers, there *is* a difference between trust of the neutral story compared to the negative story condition, where high identifiers are much less trusting of the negative story. There's some indication of motivated processing here. Furthermore, the coefficient for PSIM is slightly larger than PID and accounts for about 3% more variance (see Table 4-5). And when the interactions are run in the same model, the direct and moderating effects of PID are insignificant while the direct and moderating effects of PSIM remain highly significant. Thus, hypothesis 5 – projecting that PSIM is a stronger predictor of motivated reasoning – is also supported. The results remain even when including the full battery of controls (See Appendix Table C7).

## Discussion

Research on the hostile media effect, selective exposure and motivated reasoning has come to dominate the political media effects field. They are consistently predicted by (and/or moderated by) the traditional measure of partisanship and have important implications for political attitudes and behaviors. My selection of these three established topics in political communication was further motivated by the clear theoretical connections to Social Identity Theory. I believe previous scholarship has made a strong case for group-identity attachment playing a major role in the biased processing that underpins these behaviors, attitudes and reactions to information. Yet, I believe previous work only provided partial or indirect evidence to support those claims. Specifically, I argue that the traditional measure of partisanship used almost universally in this literature, PID, did not accurately capture the affective nature nor nuance of psychological attachment to political groups.

Thus, I hypothesized that in HME, selective exposure and motivated reasoning, the new measure proposed in Chapter 3 (PSIM) would *better* predict effects than PID, and that the direction of those effects would be in line with expectations of group-identity biased processing. I find full support for this hypothesis in HME, compelling support for this hypothesis in selective exposure behavior, and an initial indication that PSIM matters in predicting motivated reasoning. Thus, showcased with a few straightforward analyses on topics highly relevant to political media effects, I find that partisanship operationalized as social identity attachment is an improved measure over PID.

A clear limitation of the data comes from focusing solely on Republicans and Democrats in Chapters 3 and 4. This choice facilitated a narrowly focused comparison between PID and PSIM in group threat contexts. Additional testing of the PSIM measure should nevertheless



incorporate a *fully* representative sample (as in accounting for the more than 40% of Americans who report being Independent). As I mentioned in previous Chapters, this kind of investigation may highlight even further the usefulness of the measure by revealing more meaningful information about what it means to be Independent but *lean* towards one party or the other. Is it simply a variation along the continuum of psychological attachment to groups? Or is it a distinct political perspective, whereby there is no attachment to a group (or rejection of the groups), but instead a straightforward preference for certain policies?

Further, the limited results of the motivated reasoning analysis (namely that there wasn't a difference between low and high identifiers *within* the negative story condition) could be influenced by the nature of the experimental stimulus. The fact that these stories were real, and that the sample was targeted at established partisans who were likely interested in and following the campaign, it's possible that they had already been exposed to the stories and pre-established an opinion of whether they found the story credible or not. This could be accounted for in future experimental work.

And finally, None of the models in this project investigate the psychological mechanisms through which attachment to political groups has an impact on media effects outcomes. My theoretical argument rests on the idea that political elections are a context of group-identity threat opportunity, with political media as the potential vehicle of threat triggers. But I do not report whether threat, discomfort (i.e., cognitive dissonance), or affect are provoked during the process. This limitation was, in part, because I chose to highlight the PSIM/PID comparison. I believe it to be an essential precursor to investigation into the mechanisms. (Afterall, if PSIM proved to be a poor predictor of media effects compared to PID, testing its underlying mechanisms may be unnecessary.) That said, I believe the results of this chapter provide strong evidence to support

the exploration of the psychological mechanisms connected to partisan social identity attachment (and triggered by media) in future work, particularly using lab experiments.

## Chapter 5 Conclusion

A growing body of work in political science argues for the operationalization of political partisanship in the U.S. as a group-identity attachment (at least for some partisans), connecting to the expansive literature on Social Identity Theory (SIT) in psychology. Political communication research has demonstrated the importance of partisanship in predicting and moderating media effects as well, with many scholars leveraging SIT as a framework for understanding the underlying mechanisms of that relationship. The goal of this project was to bridge the study of group identity and partisanship from psychology and political science to communication studies more directly. I argued that if attachment to political parties is truly a psychological and affective condition: first, it should be measured as such; second, political elections would be a likely context for political groups to be threatened; third, it is likely that media is a vehicle for delivering group-threatening messages; and finally, thus partisanship, conceptualized in line with SIT, could help political communication researchers better understand heterogeneous media effects in politics.

In Chapter 2, I use survey data collected in real time during the past five U.S. presidential elections (2000 – 2016) alongside measures of daily fluctuations in media tone to explore the impact of media sentiment on feelings towards the presidential candidates. The chapter was designed to showcase how partisanship clearly moderates these effects. Using a traditional measure of partisanship, I find that positive feelings about the in-party candidate *increased* as negative coverage *increased* (for both Democrats and Republicans). Attitudes about the out-party candidates, in contrast, follow the tone of coverage. Furthermore, the in-party results of this

analysis were amplified for the strongest partisans. Although the measure of partisanship in this analysis was not conceptualized in line with my theoretical argument, I present it as both a demonstration of the concurrent validity of the general idea, and evidence that this dynamic occurs among real voters, during real presidential elections (not just experimentally provoked).

Chapter 3 addresses the measurement of partisanship as a social identity attachment. I review an overwhelming amount of literature in psychology that has explored the operationalization of group identities, finding more than 20 unique measures that cover about 13 different theories about the dimensions underlying this attachment. This includes a small group of scholars who have applied SIT to the measure of partisanship directly. There appears to be no clear theoretical grounding for which of the many measures would be best suited for partisanship. Thus, I test 37 different questions drawing from this work using principal components analysis and find that nearly all fall onto one dimension, and that the top ten questions (even the top four) are highly correlated with the entire 37-item battery. Most importantly, I find that the top-ten measure of partisan social identity is only mildly correlated with the traditional measure of partisanship, indicating that they are, in fact, measuring distinct concepts. I present this novel measure of SIT-focused partisanship and hypothesize that it will out-perform the common existing measure in explaining political media effects.

Such is the focus of Chapter 4. Using a two-wave survey fielded during the 2020 presidential election, I test the power of the new measure against the previous measure on three prominent areas of study in political communication: hostile media effect, selective exposure and motivated reasoning. Compared to the analysis in Chapter 2 which looks at aggregate trends, these results focus on individual reactions to experimental exposure to news about the candidates (but still during a real election context). Across the analyses, the SIT-focused measure is often an

improvement over the existing measure in predicting heterogeneous media effects. As outlined in the discussion section of this chapter, the results provide further evidence to support my argument and sufficient proof of concept to warrant continued and more rigorous testing. Below, I will highlight one final analysis as an example of how the new measure could be used to better understand the effect of media on political attitudes.

### **The Moderating Role of PSIM in Media's Effect on Attitudes**

The following analysis of media effects aims to revisit the models tested in Chapter 2 – where the impact of media coverage of in-party presidential candidates on attitudes was moderated by PID – using PSIM as well. The literature reviewed in that chapter presents evidence to suggest that media may actually affect partisans' attitudes, not just the processes through which they consume or rationalize information. A key thread throughout this project is the idea that media coverage of political elections in the U.S. is a trigger of social identity for partisans, particularly since the U.S. news industry tends to be rewarded for more competitive-focused, gamified, or “horse race” coverage between the political groups (see e.g., Searles & Banda, 2019). Thus, positive coverage of one's party or party leadership/candidate should bolster positive feelings about the group while negative coverage should be threat provoking and bring about biased information processing.

In terms of the effect on attitudes, many argue that partisan attitude thresholds are already too high or too low for media to fundamentally shift those attitudes. Although the effects reported in Chapter 2 were indeed relatively small, they still persist above and beyond a wealth of controls and the negative direction of the coefficient for in-party attitudes indicated some form of biased processing. The fact that variation in strength of PID also proves to be significant

motivates my prediction that PSIM will be a useful and potentially more potent tool to replicate these findings. I thus predict that the impact of exposure to negative information about the in-party presidential candidate on feelings of warmth towards the in-party candidate will be moderated by PSIM and PID. But PSIM will be a stronger moderator of changes in attitudes post-exposure than PID.

In both the first and second waves of the survey (used in Chapters 3 and 4), respondents were asked to rate their favorability of the two 2020 presidential candidates using the 0 – 100 numeric feeling thermometer scale. This measure is commonly used to measure attitudes by long-standing national political surveys such as the American National Election Studies. Beyond the measure's established use in the field, I selected it to also enable easier comparisons of the results between this survey and the ANES data analyzed in Chapter 2. Respondents were asked: "Please rate how you feel about President Donald Trump using the feeling thermometer below. You can choose any number between 0 and 100. The higher the number, the **warmer** or more favorable you feel toward that person, the lower the number, the **colder** or less favorable. You would rate this person at the 50-degree mark if you feel neither warm nor cold toward them." They were subsequently tasked with moving a cursor along a sliding 0 – 100 scale. In wave 1, this question is asked near the end of the survey, after the partisan social identity battery, media use, hostile media perception and selective exposure experiment. In wave 2, the feeling thermometer is tested immediately after the exposure to the negative or neutral story about the candidates (prior to perceptions of trust in the story).

In the analysis that follows, the feeling thermometer scores from wave 2 are used as a dependent variable, predicted by the negative story exposure condition, PID and PSIM. The feeling thermometer scores from wave 1 are used as a control in the models, as is a binary

variable Republican/Democrat to control for baseline differences in in-party candidate support between parties. Similar to evaluations of trust of the in-party story exposure from Chapter 3, feeling thermometer scores from both waves were collapsed into one measure each: *In-party feeling thermometer*. Thus, this variable only captures Democrats attitudes towards Biden and Republicans attitudes towards Trump.

Table 5-1 includes three OLS regression models. The first tests the direct effects of PID and PSIM without any interactions, followed by a model including interactions between the treatment and PID or PSIM. It is, first, evident that the negative exposure condition worked. Across almost all of the models, exposure to a negative story about the in-party candidate compared to a neutral story on its own predicted significantly *less feelings of warmth* towards that candidate (where PID and PSIM are zero, meaning this effect is for leaners in the second and third models that include interactions). In line with my expectations, PSIM is also a stronger predictor of changes in attitudes than PID post-exposure. In the first model, PSIM is highly significant at predicting greater feelings of warmth towards in-party candidates while PID is not.

In models 2 and 3 in Table 5-1, the coefficient on the interaction of the negative story condition with PSIM (and PID) was not significant.<sup>4</sup> It is worth noting that although the interaction fails to achieve significance, the coefficients are all in the expected direction, however. The absence of statistical significance is likely due to multicollinearity. Variance Inflation Factors indicate that the standard error for the interaction of PSIM and the exposure condition is more than three times what it might be in the (hypothetical) absence of collinearity between the variables: the VIF for the interaction coefficient is 12.6 (the square root of which is

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<sup>4</sup> The results in Table 5-1 hold when controlling for demographics, weekly media consumption and political interest.

3.5, indicating the standard error is more than three-times greater what it might be in the absence of multicollinearity).

There thus is reason to consider the interactive effects in Table 5-1, albeit cautiously. Looking at the third model (PSIM interaction), the coefficient for the impact of the negative treatment represents its effect when PSIM is equal to 0. This large negative coefficient is in line with what one would expect at low to no partisan identity attachment – the negative story significantly *decreased* feelings of warmth about the in-party candidate. PSIM on its own remains significant and positive in this model, as described above. And even as it does not reach traditional levels of statistical significance, the coefficient for the interaction of PSIM and story condition is *positive*, as expected. This indicates that as strength of identity attachment increases, the negative impact of the negative story on attitudes about the candidate is lessened.



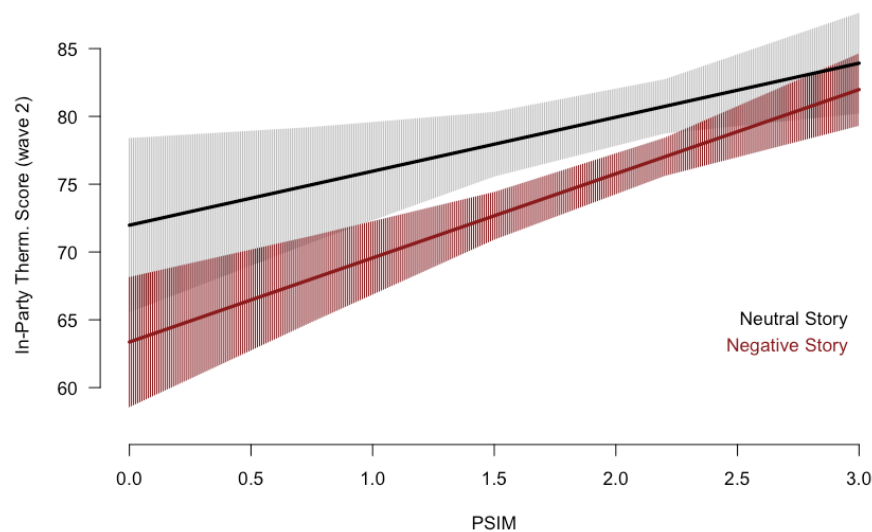
Table 5-1: Impact of Exposure on In-party Attitudes, Moderated by PSIM and PID

	Dependent variable:		
	In-party Feeling Therm. (wave2)		
	(1)	(2)	(3)
In-party feeling therm. (wave 1)	0.632*** (0.024)	0.685*** (0.021)	0.638*** (0.024)
Negative exposure	-4.252*** (1.149)	-10.849** (5.337)	-8.617** (3.709)
PID	1.352 (1.103)	1.459 (1.686)	
PSIM	5.015*** (1.093)		3.982** (1.583)
Republican	-3.361*** (1.084)	-3.306*** (1.094)	-3.499*** (1.084)
Negative Exp.*PID		2.568 (2.012)	
Negative Exp.*PSIM			2.224 (1.781)
Constant	19.925*** (2.762)	25.528*** (4.396)	25.082*** (3.139)
Observations	1,039	1,039	1,039
R <sup>2</sup>	0.573	0.565	0.573
<i>Note:</i> *p<0.1; **p<0.05; ***p<0.01			

Visualizing the effects is useful here. Figure 5-1 shows the impact of the negative (in red) compared to neutral (in grey) exposure on thermometer scores as PSIM increases. The negative treatment does lead to lower thermometer scores, *ceteris paribus*. But the difference in the negative versus neutral treatment slightly varies with PSIM. At low levels of PSIM, the negative treatment produces a sizeable downward shift in scores. At high levels of PSIM, the negative treatment appears to have almost no effect (compared to neutral). This suggests that identifiers

are not necessarily becoming more positive in response to the negative story as much as they appear to be nearly immune to the negative treatment.

*Figure 5-1: PSIM as a Moderator of the Experimental Treatment Effect on Attitudes*



These are only moderate effects, of course. And in terms of the impact of PSIM compared to PID, PID appears to moderate the effects of the experiments as effectively and in the same direction as PSIM. This is not surprising given that the findings of Chapter 2 were based on an interaction between media tone and PID. Even so, these results suggest the relative advantage of PSIM, particularly given that direct effects of PID are not significant. PSIM helps explains second-wave thermometer scores *and* moderates the impact of the experiment treatment; PID only does the latter. Even so, the relative advantages of PSIM are more evident in Chapter 4 results.

There are several reasons why the estimated moderating effect of PSIM may be muted in this analysis. First, using a partisan targeted sample may have limited the results. As in, the

respondents in wave 2 were already so deeply partisan and held such strong prior attitudes that there wasn't enough variation in the strength of attachment to see a significant moderating effect in the impact of the experiment. (The alternative was a relative lack of strong partisans, however, which would pose different difficulties.) Second, although the experiment on its own was successful at shifting attitudes about the candidates, one single exposure to one negative story may not be sufficient to demonstrate the moderating impact of PSIM on changes in attitudes. While there was clearly an attitude shift as a result of negative story exposure, increased quantity of exposure or repeated exposure may be necessary to highlight this relationship statistically. Imagine if exposure of this kind was multiplied everyday over the course of a campaign, these results might keep inching in the direction of what I find in Chapter 2, and what Redlawsk et al. (2010) find with fake political stories and candidates in an experiment.

I nevertheless regard these results as a valuable illustration of the dynamic that my research set out to explain. The analysis demonstrates, using a survey-based experimental study conducted during a real presidential election cycle, that those who identify more strongly with political parties respond differently to media content. Furthermore, it provides an additional indication that PSIM is a useful measure of this attachment beyond the traditional measure of partisanship.

## **Conclusion**

Overall, the results of the analyses in Chapters 2, 4 and above tell us that partisan *group identity attachment* matters in predicting and moderating the impact of media on voters during political elections in the U.S. Granted, there may be some instances where the traditional measure of partisanship is just as useful of a moderator – particularly if there is no theoretical

expectation of provoked group identity salience or threat. Yet in the case of multiple predominant media effects outcomes – hostile media effect, selective exposure and motivated reasoning – the new SIT-focused measure of partisan attachment is clearly more powerful. I do not suggest abandoning PID altogether. My hope was to highlight research contexts in which the PSIM measure is more effective or appropriate given the theoretical assumptions. Furthermore, the results presented in this project taken together suggest PSIM-based heterogeneity in the impact of media coverage on voter attitudes; demonstrating its usefulness and relevance to the pressing questions faced by political communication scholars today.

From the perspective of communication scholarship, it is clear that motivated processing of information is highly connected to identity attachment to the political parties. I focus my hypotheses and analyses on *directional* motivations in which that direction is dictated by group identity. From a theoretical standpoint, and as supported by previous research and the data presented here, I believe that directional motivation is the natural response to information in political election contexts given that it is an environment defined by competition between groups. Accuracy motivations have been relatively understudied, and the work that does exist indicates it can be useful in overcoming biases *when prompted* by the experimenter. Future work can, and should, dive deeper into the differences in outcomes as affected by these two motivations. For while directional appears to be a natural state for partisans during elections, it's possible to find ways in which accuracy motivations could be called on or inspired in voters.

Recall that the motivation for this research was a concern that patterns of heterogeneous reactions to negative or critical coverage of those in power may threaten the essential role of the fourth estate in our democracy. The results above suggest strong partisan identifiers are (at a minimum) inoculated from negative coverage of their in-party candidate. And evidence in

Chapter 2 suggest that more negative media coverage of the in-party candidate over the course of an entire campaign may spur strong partisans to *like their candidate even more*. Further testing of these heterogeneous effects is needed and will likely provide fascinating insight into the role group-dynamics play in understanding the media's influence on voters. In sum, I have provided evidence that the "watch-dog" role of media designed to keep those in power in check may have no impact on the voters most tied to those politicians, or even incite "boomerang" effects. This is worrisome, indeed, for if the central institution designed to aid the public in keeping leaders in check is no longer trusted, believed or effective, *how* will voters hold the government accountable?

There is no simple or straightforward solution to curing humans of our natural inclinations towards self-preservation and bias. The best to hope for is that research, such as what I've presented here, can help scholars better predict these kinds of effects and increase citizens' awareness of their biases. The former may help inspire the media to consider more careful, targeted messaging for diverse audiences, designed to improve their ability to serve as watch dogs of power. The latter is a responsibility that falls on the shoulders of citizens themselves. Arceneaux & vander Wielen (2017) find that *internal reflection* may be the only means by which partisans can recover from the deep divisions and prejudice permeating the U.S.'s current political climate. It requires voters to consciously work to overcome their biased nature in how they select information, interpret information and verify information from the media. In short, a little reflection and a little openness could do some good for democracy.

## Appendices

### Appendix A: Chapter 2 Tables

*Table A1: Interaction Model Using Panel, Cluster and OLS, Democratic Candidates*

	<i>Dependent variable:</i>	
	Dem. Cand. Feeling Thermometer	
	<i>Panel</i>	<i>OLS</i>
	<i>Estimation</i>	
Net Sent. Dem. Cand.	-1.182 (1.067)	-1.182 (1.152)
Independents PID	-21.608*** (0.581)	-21.608*** (0.580)
Republicans PID	-44.866*** (0.637)	-44.866*** (0.646)
Female	2.622*** (0.405)	2.622*** (0.406)
Black	17.643*** (0.548)	17.643*** (0.607)
Hispanic	9.525*** (0.647)	9.525*** (0.623)
Some University	1.426*** (0.448)	1.426*** (0.437)
Daily News Consumption	0.335*** (0.130)	0.335*** (0.129)
Campaign Interest	1.498*** (0.336)	1.498*** (0.321)
2004 Election (as factor)	-1.288 (1.192)	-1.288 (1.243)
2008 Election (as factor)	-0.760 (0.776)	-0.760 (0.821)
2012 Election (as factor)	-2.388*** (0.706)	-2.388*** (0.733)
2016 Election (as factor)	-14.327*** (0.855)	-14.327*** (0.869)
Net Sent. Dem. x Ind. PID	6.372*** (1.385)	6.372*** (1.443)
Net Sent. Dem. x Rep. PID	6.602***	6.602***

	(1.493)	(1.559)
Constant	69.995***	69.995***
	(0.893)	(0.909)
Observations	14,051	14,051
R <sup>2</sup>	0.490	0.490
<hr/>		
<i>Note:</i>	*p<0.05 **p<0.01 ***p<0.001	

Table A2: Interaction Model Using Panel, Cluster and OLS, Republican Candidates

	Dependent variable:	
	Republican Candidate Feeling Thermometer	
	Panel Estimation	OLS
Net Sent. Rep. Cand.	6.288*** (1.008)	6.288*** (1.028)
Independents PID	16.864*** (0.667)	16.864*** (0.664)
Republican PID	41.575*** (0.649)	41.575*** (0.732)
Female	-1.114*** (0.423)	-1.114*** (0.421)
Black	-6.712*** (0.619)	-6.712*** (0.630)
Hispanic	-2.589*** (0.655)	-2.589*** (0.646)
Some University	-3.886*** (0.461)	-3.886*** (0.452)
Daily News Consumption	0.558*** (0.138)	0.558*** (0.133)
Campaign Interest	1.483*** (0.336)	1.483*** (0.333)
2004 Election (as factor)	-2.553** (1.154)	-2.553** (1.154)
2008 Election (as factor)	-3.489*** (0.773)	-3.489*** (0.861)
2012 Election (as factor)	-9.398*** (0.689)	-9.398*** (0.750)
2016 Election (as factor)	-20.926*** (0.937)	-20.926*** (0.942)
Net Sent. Rep. x Ind. PID	-6.775*** (1.412)	-6.775*** (1.340)
Net Sent. Rep. x Rep. PID	-10.905*** (1.358)	-10.905*** (1.425)
Constant	39.265*** (0.923)	39.265*** (0.951)
Observations	14,023	14,023
R <sup>2</sup>	0.400	0.400
Note:		* ** *** p<0.01



Table A3: Impact of Media Tone\*PID on Candidates

	Dependent variable:	
	Dem. Cand. Therm.	Rep. Cand. Therm.
Net Sent. Dem. Cand.	5.294*** (1.689)	
Net Sent. Rep. Cand.		2.657* (1.520)
PID (-3)	30.107*** (0.791)	-22.353*** (0.918)
PID (-2)	16.656*** (0.828)	-10.690*** (0.971)
PID (-1)	16.864*** (0.834)	-12.157*** (0.979)
PID (1)	-15.132*** (0.894)	16.557*** (1.051)
PID (2)	-12.389*** (0.907)	17.711*** (1.062)
PID (3)	-28.786*** (0.889)	31.117*** (1.033)
Female	2.328*** (0.361)	-0.622 (0.380)
Black	13.428*** (0.551)	-2.947*** (0.580)
Hispanic	8.140*** (0.552)	-1.106* (0.582)
Some University	0.708* (0.389)	-3.516*** (0.409)
Daily News Consumption	0.407*** (0.115)	0.527*** (0.121)
Campaign Interest	1.352*** (0.290)	1.455*** (0.306)
2004 Election (as factor)	-1.832* (1.098)	-1.547 (1.035)
2008 Election (as factor)	-0.716 (0.715)	-2.838*** (0.763)
2012 Election (as factor)	-2.451*** (0.639)	-9.161*** (0.664)
2016 Election (as factor)	-14.520*** (0.765)	-20.657*** (0.842)
Net Sent. Dem. x PID (-3)	-7.162*** (2.023)	
Net Sent. Dem. x PID (-2)	-5.467** (2.163)	
Net Sent. Dem. x PID (-1)	-4.825** (2.110)	
Net Sent. Dem. x PID (1)	1.942	

	(2.253)	
Net Sent. Dem. x PID (2)	-1.071	
	(2.289)	
Net Sent. Dem. x PID (3)	-0.821	
	(2.190)	
Net Sent. Rep. x PID (-3)		5.127***
		(1.828)
Net Sent. Rep. x PID (-2)		1.512
		(1.983)
Net Sent. Rep. x PID (-1)		2.373
		(2.016)
Net Sent. Rep. x PID (1)		-6.032***
		(2.076)
Net Sent. Rep. x PID (2)		-4.769**
		(2.102)
Net Sent. Rep. x PID (3)		-8.274***
		(1.994)
Constant	47.301***	54.981***
	(0.894)	(0.987)
Observations	14,927	14,888
R <sup>2</sup>	0.567	0.474
<hr/>		
<i>Note:</i>		* p < 0.1 ** p < 0.05 *** p < 0.01

Table A4: Impact of Media Tone\*PID on Attitudes towards Democrats, by Media Consumption

	Dependent variable:	
	Dem. Cand. Feeling Thermometer (Low Media Consumption)	(High Media Consumption)
Net Sent. Dem. Cand.	3.579* (1.924)	6.929* (3.751)
PID (-3)	28.107*** (0.891)	34.897*** (1.793)
PID (-2)	15.592*** (0.910)	20.238*** (2.018)
PID (-1)	16.132*** (0.917)	19.140*** (2.029)
PID (1)	-13.135*** (1.013)	-19.123*** (1.975)
PID (2)	-12.319*** (1.009)	-12.201*** (2.126)
PID (3)	-28.539*** (1.020)	-27.991*** (1.935)
Female	2.215*** (0.434)	2.386*** (0.647)
Black	14.488*** (0.638)	11.368*** (1.092)
Hispanic	8.175*** (0.630)	8.448*** (1.134)
Some University	0.467 (0.454)	1.367* (0.750)
Daily News Consumption	1.667*** (0.322)	1.319** (0.550)
Campaign Interest	-1.965 (1.224)	-2.322 (2.846)
2004 Election (as factor)	-0.217 (0.784)	-2.795 (2.028)
2008 Election (as factor)	-1.746** (0.721)	-4.764*** (1.400)
2012 Election (as factor)	-15.039*** (1.018)	-14.878*** (1.347)
Net Sent. Dem. x PID (-3)	-3.301 (2.368)	-9.237** (4.276)
Net Sent. Dem. x PID (-2)	-3.659 (2.466)	-5.567 (4.813)
Net Sent. Dem. x PID (-1)	-2.939 (2.395)	-6.736 (4.767)
Net Sent. Dem. x PID (1)	2.031 (2.656)	-1.944 (4.641)
Net Sent. Dem. x PID (2)	0.327 (2.599)	-3.469 (5.109)

Net Sent. Dem. x PID (3)	-1.023 (2.542)	0.095 (4.618)
Constant	48.010*** (0.962)	48.906*** (1.988)
Observations	10,226	4,701
R <sup>2</sup>	0.530	0.620
<i>Note:</i>		*p<0.05 **p<0.01 ***p<0.001

Table A5: Impact of Media Tone\*PID on Attitudes towards Republicans, by Media Consumption

	Dependent variable:	
	Rep. Cand. Feeling Thermometer (Low Media Consumption)	(High Media Consumption)
Net Sent. Rep. Cand.	3.564* (1.891)	6.325** (2.842)
PID (-3)	-20.481*** (1.015)	-29.493*** (2.098)
PID (-2)	-9.441*** (1.047)	-17.363*** (2.423)
PID (-1)	-10.098*** (1.057)	-22.018*** (2.400)
PID (1)	16.291*** (1.166)	15.614*** (2.358)
PID (2)	18.944*** (1.164)	11.023*** (2.496)
PID (3)	30.308*** (1.169)	30.462*** (2.238)
Female	-0.334 (0.448)	-1.373* (0.704)
Black	-2.715*** (0.662)	-4.060*** (1.188)
Hispanic	-0.485 (0.653)	-3.850*** (1.236)
Some University	-2.225*** (0.469)	-6.521*** (0.816)
Daily News Consumption	1.481*** (0.333)	2.818*** (0.600)
Campaign Interest	-1.153 (1.155)	-5.879** (2.818)
2004 Election (as factor)	-2.987*** (0.829)	-3.281 (2.214)
2008 Election (as factor)	-9.456*** (0.745)	-8.471*** (1.489)
2012 Election (as factor)	-19.605*** (1.127)	-19.997*** (1.455)
Net Sent. Rep. x PID (-3)	3.095 (2.338)	0.163 (3.338)
Net Sent. Rep. x PID (-2)	-0.386 (2.447)	-2.589 (3.840)
Net Sent. Rep. x PID (-1)	1.417 (2.469)	-5.728 (3.905)
Net Sent. Rep. x PID (1)	-6.779** (2.689)	-6.487* (3.712)
Net Sent. Rep. x PID (2)	-6.244** (2.698)	-9.433** (3.837)

Net Sent. Rep. x PID (3)	-8.112*** (2.629)	-8.939** (3.511)
Constant	54.456*** (1.048)	63.123*** (2.243)
Observations	10,193	4,695
R <sup>2</sup>	0.436	0.536
<i>Note:</i>		* p < 0.05 ** p < 0.01 *** p < 0.001

## Appendix B: Chapter 3 Measures and Tables

Table B1: Social Identity Measure Questions by Author

Author(s)	Theoretical Construct	Question wording
Mael and Tetrick (1992)	Shared experience	When someone criticizes () it feels like a personal insult.
Greene (2004)		I'm very interested in what others think about ()
		When I talk about (), I usually say "we" rather than "they"
		()'s successes are my successes.
		When someone praises (), it feels like a personal compliment.
		I act like a () person to a great extent.
	Shared characteristics	If a story in the media criticized (), I would feel embarrassed.
		I don't act like a typical () person.
		I have a number of qualities typical of () people.
		The limitation associated with () people apply to me also.
Ashmore et al. (2004) <i>theory</i>	Self-categorization	Do you identify as a member of ()?
Heere and James (2007), Heere et al. (2011) <i>applied</i>		
	Private evaluation	I feel good about being a member of ().
		In general, I am glad to be a ().
		I'm proud to think of myself as a ().
	Public evaluation	Overall, () are viewed positively by others.
		In general, others respect ().
		Overall, people hold a favorable opinion about ().
	Sense of interdependence	What happens to () will influence what happens in my life.
		Changes affecting () will have an impact on my own life.
		What happens to () will impact my own life.
	Interconnection of self with group	When someone criticizes () it feels like a personal insult.

		In general, being associated with () is an important part of my self-image.
		When someone compliments (), it feels like a personal compliment.
	Behavioral involvement	I participate in activities supporting ().
		I am actively involved in activities that related to ().
		I participate in activities with other ().
	Cognitive Awareness/meaning	I am aware of the tradition and history of ().
		I know the ins and outs of ().
		I have knowledge of the successes and failures of ().
Huddy et al. (2015)	Affective partisanship (a)	How important is being () to you?
		How well does the term () describe you?
		When talking about (), how often do you use "we" instead of "they"?
		To what extent do you think of yourself as being a ()?
Bankert, Huddy and Rosema (2017)	Affective partisanship (b)	I am interested in what other people think about this party.
		I have a lot in common with other supporters of this party.
		If this party does badly in opinion polls, my day is ruined.
		When I speak about this party, I usually say "we" instead of "they".
		When people criticize this party, it feels like a personal insult.
		When I meet someone who supports this party, I feel connected with this person.
		When I speak about this party, I refer to them as "my party".
		When people praise this party, it makes me feel good.
Kelly (1988)	Positive affect	It is important to me that I support this party.
Brown and Williams (1984)		I identify with this party.
		I feel strong ties with other people who support this party.
		I am glad to support this party.
		I see myself as supporting this party.
	Negative affect	I make excuses for supporting this party.
		I try to hide supporting this party.



		I feel that it puts me at a disadvantage to support this party.
		I feel annoyed to say I support this party.
		I feel critical of this party.
Martin et al. (1997)	Social identity	Most of my friends are ().
<i>applied to identification as an athlete</i>		Other people see me mainly as ().
	Self-identity	I consider myself a ().
		I have many goals related to ().
	Negative affectivity	I feel bad about myself when () does poorly.
		I would be very depressed if () failed.
	Exclusivity	() is an important part of my life.
		I spend more time thinking about () than other things.
Kashima et al. (2000)	Group identification	I am proud to belong to ().
		I feel strong ties with ().
		I am glad that I belong to ().
		Being a () is an important reflection of who I am.
		Being a () is an important part of my self-image.
		() is very important to me.
	Self-typicality	Others would describe me as ().
		I feel I am a typical ().
		My background is similar to that of most ().
		Most () think and behave differently than me.
		I do not look like a typical ().
		My values are very different from those of most ().
Cameron (2000)	Ingroup ties	I have a lot in common with other ().
		I feel strong ties to other ().
		I find it difficult to form a bond with other ().
		I don't feel a sense of being "connected" with other ().
		I really "fit in" with other ().
		In a group of (), I really feel that I belong.
	Centrality	I often think about the fact that I am ().
		Overall, being () is an important part of my self-image.
		The fact that I am () rarely enters my mind.

		I am not usually conscious of the fact that I am ().
		Being () is an important reflection of who I am.
		In my everyday life, I often think about what it means to be ().
	Ingroup affect	In general, I'm glad to be a ().
		I often regret that I am a ().
		I don't feel good about being a ().
		Generally, I feel good when I think about myself as a ().
		Just thinking about the fact that I am a () sometimes gives me bad feelings.
Sellers et al. (1998)	Centrality	Overall, being () has very little to do with how I feel about myself.
		In general, being () is an important part of my self image.
		My destiny is tied to the destiny of other ().
		Being () is unimportant to my sense of what kind of a person I am.
		I have a strong sense of belonging to ().
		I have a strong attachment to other (s).
		Being () is an important reflection of who I am.
		Being () is not a major factor in my social relationships.
	Private regard	I feel good about ().
		I am happy that I am ().
		I feel that () have made major accomplishments and advancements.
		I often regret that I am ().
		I am proud to be ().
		I feel that the () community has made valuable contributions to this society.
	Public regard	Overall, () are considered good by others.
		In general, others respect ().
		Most people consider (), on the average, to be more ineffective than other political groups.
		() are not respected by the broader society.
		In general, other people view () in a positive manner.
		Society views () as an asset.
Leach et al. (2008)	<b>Self-investment</b>	
	Solidarity	I feel a bond with ().
		I feel solidarity with ().
		I feel committed to ().
	Satisfaction	I'm glad to be ().

		I think that () have a lot to be proud of.
		It is pleasant to be ().
		Being () gives me a good feeling.
	Centrality	I often think about the fact that I am ().
		The fact that I am () is an important part of my identity.
		Being () is an important part of how I see myself.
	<b>Self-Definition</b>	
	Individual self-stereotyping	I have a lot in common with the average () person.
		I am similar to the average ().
	In-group homogeneity	() people have a lot in common with each other.
		() people are very similar to each other.
Jackson (2002)	Affective ties	() can always count on each other.
		Most() would take a substantial risk to rescue me.
		If I were in trouble, a () member would help me.
		() is united.
		I would take substantial risk to rescue () member in trouble.
		In a time of personal need, I can rely on ().
		If a () were in trouble, I would help him or her.
		When I am with (), I usually feel like we are one unit.
		There is a feeling of unity among ().
		()'s successes are my successes.
		() need to stick together.
		() is more like a collection of separate individuals than a whole.
		Even if () is not doing well, it is important that we stick together.
		It is important for () to be loyal to individual members.
		When members of () do well, I feel good.
		It is important for individual members to be loyal to ().
		I enjoy working with other () to achieve success.
		Regarding (), it is accurate to say "United we stand, divided we fall."
		When I am with (), I feel like we are separate individuals.
		I feel a kinship of sorts with other ().
		When () fails, I feel depressed.
		When I talk about (), I say "we" rather than "they".
		When difficult problems arise, I can not count on ().
		If a story in the media criticized (), I would feel embarrassed.

	Attraction to ingroup (evaluative)	I am glad I am ().
		I am proud to be a member of ().
		I feel () is <i>not</i> worthwhile.
		I attach great value to my () membership.
		It is good to be a ().
		I would <i>not</i> feel badly if I had to leave ().
		My image of the () is negative.
		I don't really feel like a part of ().
		I am a typical ().
		I support the ().
		I don't act like a typical ().
		I live my life as independently from ()s as possible.
		I regret being a member of ().
		It puts me at a disadvantage to be a ().
		My opinions are usually consistent with ().
		I feel uneasy with other ().
		Overall, I am proud of being ().
		I have a number of qualities typical of () people.
		I often exhibit my positive feelings about ().
		I feel that my everyday interests are <i>not</i> in line with most ().
	Self-categorization (cognitive)	I am a ().
		Being () is an important part of my self-identity.
		My () membership is important to the way I view myself.
		Being a () is an important reflection of who I am.
		() have a number of things in common with each other.
		People in the (outgroup) are a lot alike in many respects.
		It is important to me that others identify me as ().
		I prefer to see (ingroup) as distinct from (outgroup).
		I am very interested in what others think about ().
		(outgroup) people are different from (ingroup) people.
		I act like a () to a great extent.
		Any limitations associated with () tend to apply to me too.

*Table B2: Social Identity Measure Theoretical Constructs, By Author*

<b>Theoretical Construct</b>	<b>Author (s)</b>	<b># authors</b>
Shared experience	Mael and Tetrick (1992) Greene (2004)	2
Shared characteristics / self-typicality / self-stereotyping (Self-definition, Leach)	Mael and Tetrick (1992) Greene (2004) Kashima et al. (2000) Leach et al. (2008)	4
Self-categorization	Ashmore et al. (2004) Heere and James (2007) Heere et al. (2011) Martin et al. (1997) Jackson (2002)	5
Private evaluation	Ashmore et al. (2004) Heere and James (2007) Heere et al. (2011) Sellers et al. (1998) Jackson (2002)	5
Public evaluation	Ashmore et al. (2004) Heere and James (2007) Heere et al. (2011) Sellers et al. (1998) Jackson (2002)	5
Sense of interdependence	Ashmore et al. (2004) Heere and James (2007) Heere et al. (2011)	3
Interconnection with group and self / intergroup ties	Ashmore et al. (2004) Heere and James (2007) Heere et al. (2011) Cameron (2004)	4
Behavioral involvement	Ashmore et al. (2004) Heere and James (2007) Heere et al. (2011)	3
Cognitive awareness / meaning	Ashmore et al. (2004) Heere and James (2007) Heere et al. (2011)	3
Positive affect	Huddy et al. (2015) Bankert et al. (2017) Kelly (1988) Cameron (2000) Jackson (2002)	5
Negative affect	Huddy et al. (2015) Bankert et al. (2017) Kelly (1988) Cameron (2004) Martin et al. (1997) Jackson (2002)	6
Exclusivity	Martin et al. (1997)	1
Group identification	Kashima et al. (2000)	1
Centrality (Self-investment, Leach)	Cameron (2004) Sellers et al. (1998) Leach et al. (2008)	3
Solidarity (Self-investment, Leach)	Leach et al. (2008)	1
Satisfaction (Self-investment, Leach)	Leach et al. (2008)	1
In-group homogeneity (Self-definition, Leach)	Leach et al. (2008)	1

*Table B3: Proportion of Variance Explained, Various Number of Constrained Factors*

<b>Non-Rotated</b>		<b>Varimax Rotated</b>			
# Factors	Prop. Variance Explained (PVE)	# Factors	PVE Factor 1	PVE Factor 2	PVE Factor 3
3	0.443	3	0.249	0.22	
4	0.443	4	0.192	0.162	0.159
5	0.444	5	0.17	0.163	0.156
6	0.445	6	0.16	0.155	0.125
7	0.445	7	0.151	0.137	0.128
13	0.447	13	0.142	0.136	

Most of the analyses conducted by the authors reviewed in this chapter use constrained factor analysis in order to test a pre-designed theoretical, multidimensional model of measuring social identity attachment. I focused on a data-driven approach, rather than theoretical and thus used unconstrained principal components analysis to examine the relationship among the 37 questions fielded to measure partisan social identity. In the effort of comparison, I've also run the 37-item battery using constrained factor analysis. I ran this analysis multiple times using from three to seven, and then using 13 different constrained factors. The proportion of variance explained by the various number of factor models is reported in Table B3. For the non-rotated models, the results remain the same regardless of how many factors are considered. For the rotated models, there is at most three factors that cover about equal amount of variance regardless of how many other factors are forced. All other factors cover less than 10% of the variance. Thus, the results reported in Tables B4 and B5 are for a three-factor constrained analysis due to the similarity in results across any number of pre-selected factors.

The first factor analysis reported in Table B4 is non-rotated. The results of this analysis are very similar to the results reported above using un-restricted PCA. Most of the survey questions load onto the first factor, which accounts for almost half of all variance. This replicates the one-factor solution. The second analysis reported in Table B5 is a varimax rotation with the three constrained factors. In this analysis, I find that the first and second factors explain about the

same amount of variance (about a quarter). If you look at the factor loadings more closely, it appears there's much variation within theoretical constructs. For example, behavior 1 spreads almost evenly across the first two factors while behavior 2 loads more strongly on the second factor. Qualitatively, it appears the factors loading on the first versus second dimensions lack any kind of meaningful pattern or theoretical justification. This is also true across the models including an additional number of factors. Thus, I take this as further evidence that even when "forcing" the loadings into multiple factors, little meaning is gleaned.

Table B4: Factor Analysis of Partisan Social Identity Measure Questions, Non-rotated

Variable	Factor 1	Factor 2	Factor 3
Affect1	0.761	-0.380	
Affect2	0.746	-0.429	
Affect3	0.761	-0.393	
Affect4		-0.685	
Behavior1	0.732		0.101
Behavior2	0.671	0.261	
Importance1	0.823		-0.222
Importance2	0.808	0.111	-0.285
Importance3	0.796		-0.278
Solidarity1	0.796		
Solidarity2	0.793		
Solidarity3	0.804	-0.150	-0.146
Typicality1	0.699		0.247
Typicality2	0.729	-0.135	0.223
Typicality3	0.656		0.206
Knowledge1	0.610		0.234
Knowledge2	0.658	0.180	0.150
Knowledge3	0.641	0.104	0.222
CommonFate1	0.676	0.223	-0.134
CommonFate2	0.762		
CommonFate3	0.732	0.166	
CommonFate4	0.492	0.482	
CommonFate5	0.608	0.152	
Homogeny1	0.700		0.116
Homogeny2	0.662		0.128
Cognitive1	0.661	0.327	-0.136
Cognitive2		-0.235	-0.274
Attitude1	0.581	0.371	
Attitude2	0.615	0.171	0.198
Attitude3	0.594	0.172	0.222
Attitude4	0.651	-0.259	0.177
ExternalEvaluation1	0.681	0.124	0.129
ExternalEvaluation2	0.745	0.202	
Distinction1	0.655		
Distinction2	0.552		
Social1	0.577		0.218
Social2	-0.120		-0.334
<i>SS Loadings</i>	16.396	1.995	0.998
<i>Proportion of Variance</i>	0.443	0.054	0.027
<i>Cumulative Variance</i>	0.443	0.497	0.524



Table B5: Factor Analysis of Partisan Social Identity Measure Questions, Varimax Rotated

Variable	Factor 1	Factor 2	Factor 3
Affect1	0.822	0.225	
Affect2	0.839	0.193	
Affect3	0.825	0.232	
Affect4	0.373	-0.460	-0.365
Behavior1	0.534	0.455	0.234
Behavior2	0.334	0.585	0.257
Importance1	0.534	0.455	0.234
Importance2	0.334	0.585	0.257
Importance3	0.637	0.566	-0.107
Solidarity1	0.583	0.545	
Solidarity2	0.618	0.496	
Solidarity3	0.675	0.481	
Typicality1	0.592	0.314	0.322
Typicality2	0.662	0.292	0.275
Typicality3	0.460	0.396	0.335
Knowledge1	0.432	0.353	0.351
Knowledge2	0.393	0.479	0.322
Knowledge3	0.441	0.390	0.354
CommonFate1	0.338	0.635	
CommonFate2	0.512	0.556	0.129
CommonFate3	0.426	0.610	0.127
CommonFate4		0.648	0.233
CommonFate5	0.353	0.490	0.167
Homogeny1	0.544	0.398	0.223
Homogeny2	0.422	0.474	0.246
Cognitive1	0.259	0.693	0.122
Cognitive2		-0.349	
Attitude1	0.189	0.617	0.243
Attitude2	0.374	0.426	0.354
Attitude3	0.361	0.403	0.372
Attitude4	0.678	0.181	0.171
ExternalEvaluation1	0.444	0.467	0.285
ExternalEvaluation2	0.410	0.647	0.132
Distinction1	0.513	0.376	0.176
Distinction2	0.392	0.352	0.189
Social1	0.423	0.321	0.320
Social2		-0.355	
<i>SS Loadings</i>	9.214	8.122	2.053
<i>Proportion of Variance</i>	0.249	0.220	0.055
<i>Cumulative Variance</i>	0.249	0.469	0.524

## Appendix C: Chapter 4 Experimental Stimulus and Tables

*Figure C1: Negative Stories about President Trump*

### Negative Story 1

Please read the following news story:

#### **Trump Quotes Fascist Dictator in Latest Twitter Gaffe**

**Washington, D.C.** — Since entering the White House in 2017, President Donald Trump has been highly criticized for his repeated blunders and typos posted to his personal Twitter account, @realDonaldTrump. He's now facing controversy again after he posted a quote originally spoken by fascist Italian dictator Benito Mussolini. President Trump re-tweeted a post from the account @ilduce2016 with the following quote: "It is better to live one day as a lion than 100 years as a sheep."

Benito Mussolini took power in Italy in the early 1920's and was allied with Germany's Adolf Hitler during WWII, until being toppled from power in 1943 as Allied forces fought their way up Italy. President Trump has come under scrutiny as he often has declined to distance himself or reject the support of extreme, far-right leaders and ideas. It's unclear whether this latest gaffe will have any negative implications for the President among voters.

### Negative Story 2

Please read the following news story:

#### **Trump's Latest Blunder, Confusing 9/11 with 7 Eleven**

**Buffalo, Ny.** — Since the beginning of his run for office, President Donald Trump has been highly criticized for his repeated blunders, inappropriate comments and typos posted to his personal Twitter account, @realDonaldTrump. He's now facing controversy again after he mistakenly referred to the terrorist attacks that took place on September 11 in New York City as "7/11" rather than "9/11."

At a rally in Buffalo, New York, he said, "I was down there and I watched our police and our firemen down there on 7/11." The September 11 terror attack was an event that changed the course of history in America. Many in the crowd were surprised that President Trump so carelessly, and mistakenly, referred to the popular convenience store chain "7 Eleven" without correcting himself at the time. It's unclear whether this latest gaffe will have any negative implications for the President among voters.

*Figure C2: Negative Stories about (then candidate) President Biden*

### **Negative Story 1**

Please read the following news story:

#### **Biden's Latest Racial Blunder Under Scrutiny**

**Des Moines, Ia.** — Former Vice President Joe Biden comes under scrutiny again in his latest blunder during a speech on the campaign trail in Iowa. Biden made the audience very uncomfortable when he said, “poor kids are just as bright and just as talented as white kids.” This isn’t the first time the Democratic presidential nominee has faced intense criticism for his record on race and for his verbal missteps.

Mr. Biden was speaking on education and the need to challenge students at a town hall hosted by the Asian & Latino Coalition when he made the remark, and it has quickly circulated among social media and news television stations. This comes just days after facing controversy for having highlighted his ability to work with segregationist senators back in the 1970’s and 1980’s. In the past, Biden has been seen as a generally well-liked candidate among Black American voters. It’s unclear whether this gaffe will negatively affect that support.

### **Negative Story 2**

Please read the following news story:

#### **Biden's Latest Gaffe, Running for Senate instead of President**

**Toledo, Oh.** — Former Vice President Joe Biden comes under scrutiny again in his latest blunder during a speech on the campaign trail in Ohio. Biden made the audience very uncomfortable when he said, “That’s why I’m running. I’m running as a proud Democrat for the Senate,” instead of President. This isn’t the first time the Democratic presidential nominee has faced intense criticism for his verbal missteps, and what at times appears to be poor memory.

Mr. Biden was speaking to a crowd of manufacturing workers about the loss of jobs in the region and suffering economy when he made the remark, and it has quickly circulated among social media and news television stations. Critics frame this latest careless mistake within the broader concerns young voters in particular have about whether he’s “too old” to be running for office. It’s unclear whether this gaffe will negatively affect that support.

*Figure C3: Neutral Stories about President Trump and President Biden*

***President Trump***

Please read the following news story:

**Trump Campaign Headed to Michigan**

**Detroit, Mi.** — President Donald Trump will be back in Michigan, starting a week-long tour of the midwest -- a key region where he mostly swept electoral votes in the 2016 election, and one that will be essential to secure in November. The kickoff event will be held at an airport hangar near Saginaw, followed by events in Detroit and Grand Rapids before heading to Ohio.

Trump last made a stop in Michigan a few months ago, where he visited Ford Motor Co.'s Rawsonville Components Plant and spoke to union workers. On this trip, representatives from the Trump campaign said he plans to discuss job creation and protection of the manufacturing industry. First Lady Melania Trump will join the President, along with their son, Barron.

**(then candidate) President Biden**

Please read the following news story:

**Biden Campaign Headed to Pittsburgh**

**Latrobe, Pa.** — The former vice president and Democratic presidential nominee, Joe Biden, who estimates he's logged more than 2.1 million miles riding the rails in his lifetime, added seven more hours to that total Wednesday as his campaign chartered a private train to tour parts of eastern Ohio and western Pennsylvania - key areas to pick up votes if he wants to flip the states from red to blue in November.

Biden spent much of the trip inside a window-lined "conversation car" chatting with supporters he had picked up at stops along the way. He and his wife, Jill, also had their own all-glass space at the back of the train known as the "president's car." The tour, which will be focused on the economy and working families, will be Mr. Biden's first trip to the area since formally accepting the Democratic Party's nomination.

Table C1: Hostile Media Effect, PSIM vs. PID, with controls

	<i>Dependent variable:</i>		
	HME, Wave 1		
	(1)	(2)	(3)
PSIM		0.502*** (0.042)	0.519*** (0.047)
PID	0.196*** (0.046)		-0.041 (0.050)
Political interest	0.248*** (0.025)	0.171*** (0.025)	0.172*** (0.025)
Female	-0.018 (0.052)	-0.031 (0.051)	-0.030 (0.051)
University	-0.036 (0.053)	-0.023 (0.051)	-0.025 (0.051)
Black	-0.329*** (0.074)	-0.362*** (0.072)	-0.361*** (0.072)
Age	-0.065*** (0.016)	-0.051*** (0.016)	-0.051*** (0.016)
Weekly Media Consumption	-0.006 (0.005)	-0.009* (0.005)	-0.009* (0.005)
Constant	1.757*** (0.148)	1.430*** (0.118)	1.500*** (0.146)
Observations	2,217	2,217	2,217
R <sup>2</sup>	0.087	0.135	0.135
<i>Note:</i>	*p<0.1; **p<0.05; ***p<0.01		

Table C2: Predicting Hostile Media Effect by Party

	<i>Dependent variable:</i>					
	Republican HME			Democrat HME		
PID	0.467*** (0.058)		0.139** (0.065)	0.172*** (0.060)		-0.149** (0.065)
PSIM		0.617*** (0.048)	0.556*** (0.056)		0.546*** (0.052)	0.609*** (0.058)
Constant	1.810*** (0.156)	1.773*** (0.103)	1.535*** (0.152)	1.600*** (0.162)	0.953*** (0.109)	1.220*** (0.160)
Observations	1,131	1,131	1,131	1,190	1,190	1,190
R <sup>2</sup>	0.054	0.127	0.131	0.007	0.086	0.090
<i>Note:</i>				*p<0.1; **p<0.05; ***p<0.01		

Table C3: Predicting Selective Exposure of Trump Headlines, Binomial Logit Regression

	<i>Dependent variable:</i>					
	Selecting Positive Trump Headline					
	Republicans			Democrats		
PID	0.502*** (0.110)		0.281** (0.128)	-0.411*** (0.110)		-0.161 (0.126)
PSIM		0.511*** (0.099)	0.385*** (0.114)		-0.558*** (0.102)	-0.490*** (0.115)
Constant	-0.506* (0.289)	-0.229 (0.205)	-0.706** (0.297)	0.216 (0.292)	0.243 (0.209)	0.530* (0.304)
Observations	1,131	1,131	1,131	1,190	1,190	1,190
Log Likelihood	-690.965	-687.612	-685.213	-717.484	-709.206	-708.386
Akaike Inf. Crit.	1,385.929	1,379.224	1,376.427	1,438.968	1,422.412	1,422.772
<i>Note:</i>				*p<0.1; **p<0.05; ***p<0.01		

Table C4: Predicting Selective Exposure of Biden Headlines, Binomial Logit Regression

	<i>Dependent variable:</i>					
	Selecting Positive Biden Headlines					
	Republicans			Democrats		
PID	-0.397*** (0.110)		-0.265** (0.128)	0.258** (0.109)		0.086 (0.124)
PSIM		-0.346*** (0.097)	-0.227** (0.113)		0.367*** (0.099)	0.331*** (0.112)
Constant	0.252 (0.290)	-0.081 (0.204)	0.369 (0.296)	0.046 (0.291)	-0.010 (0.205)	-0.162 (0.300)
Observations	1,131	1,131	1,131	1,190	1,190	1,190
Log Likelihood	-697.982	-698.092	-695.953	-749.243	-745.096	-744.858
Akaike Inf. Crit.	1,399.963	1,400.184	1,397.906	1,502.487	1,494.193	1,495.715
<i>Note:</i>				*p<0.1; **p<0.05; ***p<0.01		

Table C5: Predicting Selective Exposure of Trump Headlines, PSIM vs. PID, with controls

	<i>Dependent variable:</i>	
	Selecting Positive Trump Headline	
	Republicans	Democrats
PSIM	0.105*** (0.026)	-0.093*** (0.026)
PID	0.068** (0.029)	-0.040 (0.027)
Political interest	-0.013 (0.014)	-0.001 (0.014)
Female	0.128** (0.030)	0.037 (0.027)
University	-0.060** (0.029)	-0.031 (0.028)
Black	-0.164*** (0.061)	0.052 (0.034)
Age	0.019* (0.010)	-0.030*** (0.008)
Weekly Media Consumption	-0.002 (0.003)	-0.001 (0.003)
Constant	0.256*** (0.088)	0.699*** (0.077)
Observations	1,075	1,142
R <sup>2</sup>	0.068	0.043
Note:	*p<0.1; **p<0.05; ***p<0.01	



Table C6: Predicting Selective Exposure of Biden Headlines, PSIM vs. PID, with controls

	<i>Dependent variable:</i>	
	Republicans	Democrats
PSIM	-0.073*** (0.026)	0.083*** (0.027)
PID	-0.049* (0.029)	0.023 (0.028)
Political interest	-0.006 (0.014)	-0.003 (0.014)
Female	-0.074** (0.031)	-0.005 (0.028)
University	-0.014 (0.029)	-0.017 (0.029)
Black	0.061 (0.062)	-0.135*** (0.035)
Age	-0.048*** (0.010)	0.012 (0.009)
Weekly Media Consumption	0.003 (0.003)	0.001 (0.003)
Constant	0.805*** (0.089)	0.453*** (0.079)
Observations	1,075	1,142
R <sup>2</sup>	0.039	0.027
Note:	* p<0.1; ** p<0.05; *** p<0.01	

Table C7: Predicting Trust of In-party Story, Moderated by PSIM/PID, with controls

	<i>Dependent variable:</i>		
	Trust of In-party Story		
	(1)	(2)	(3)
Negative exposure	0.074 (0.393)	0.096 (0.274)	0.242 (0.395)
PID	0.377*** (0.122)		0.040 (0.141)
PSIM		0.638*** (0.110)	0.619*** (0.129)
Political interest	0.056 (0.040)	0.009 (0.041)	0.009 (0.041)
Female	0.161* (0.085)	0.154* (0.083)	0.153* (0.084)
University	0.003 (0.085)	0.011 (0.084)	0.010 (0.084)
Black	0.299** (0.131)	0.264** (0.130)	0.266** (0.130)
Age	-0.136*** (0.027)	-0.132*** (0.027)	-0.132*** (0.027)
Weekly Media Consumption	-0.005 (0.008)	-0.004 (0.008)	-0.004 (0.008)
Neg exp.*PID	-0.315** (0.148)		-0.086 (0.171)
Neg exp.*PSIM		-0.425*** (0.131)	-0.386** (0.154)
Constant	0.173 (0.344)	-0.010 (0.265)	-0.074 (0.344)
Observations	994	994	994
R <sup>2</sup>	0.111	0.136	0.137
<i>Note:</i>	*p<0.1; **p<0.05; ***p<0.01		

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